Research on Neutron/X-ray Noise and Artifact Removal Methods Based on Semantic Aggregation

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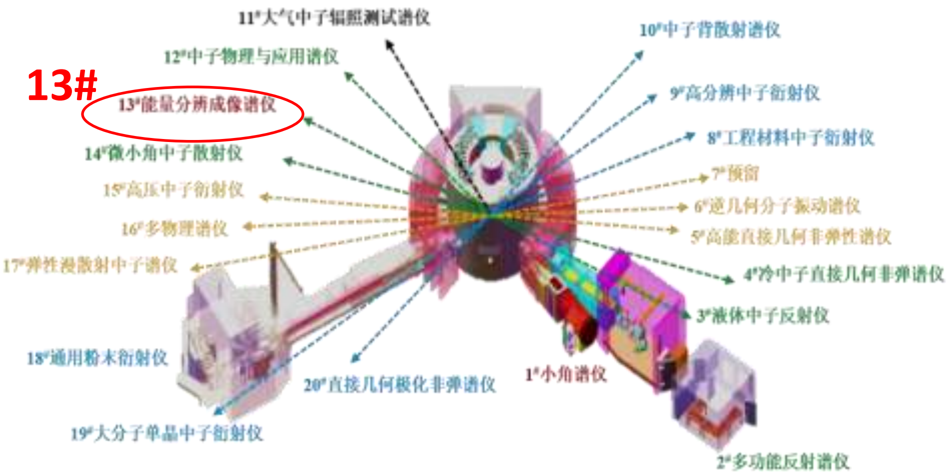
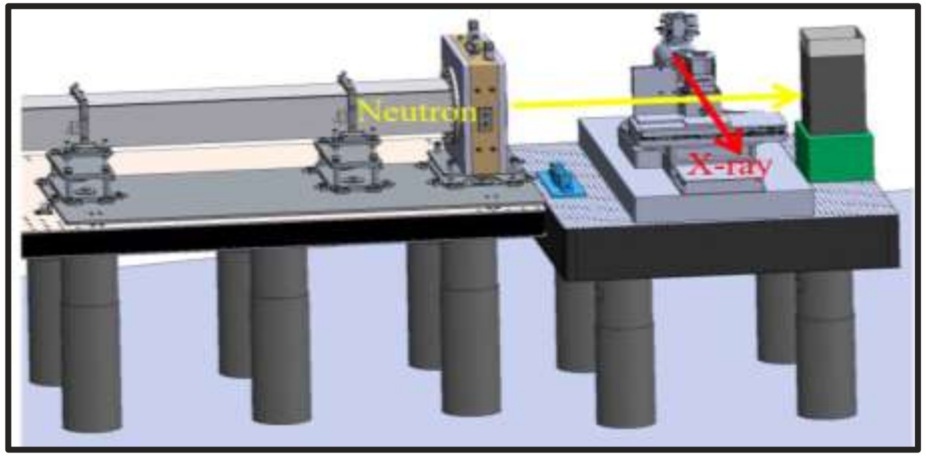
01. Background

Background



13# Energy Resolved Neutron Imaging Instrument (ERNI)



Neutron/X-ray Dual-Modality Imaging System

CT Scan Data Processing Workflow

0. Data Collection
1. Signal Enhancement
2. Domain Translation
3. Data Fitting
4. Postprocessing
5. Analysisg

Postprocessing

- Noise and Artifact Removal
- Super-Resolution
- Dual Modal Image Fusion

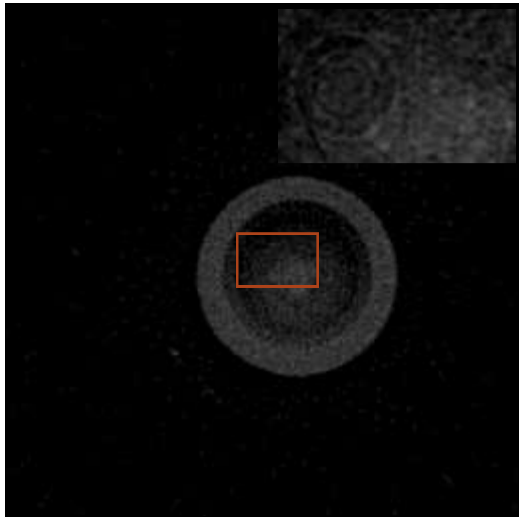
Background

■ **Sparse-view sampling offer significant benifits for CT scan**

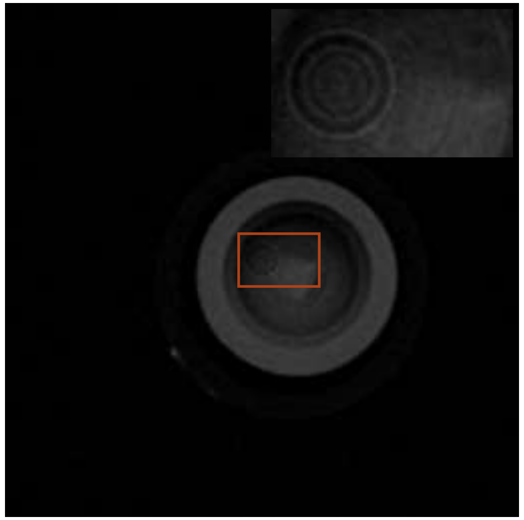
- ➢ Reduce scanning time and improve experimental efficiency.
- ➢ Reduce radiation exposure.
- ➢ Less data storage space and data transfer pressure.

■ **Sparse-view reconstruction imaging quality**

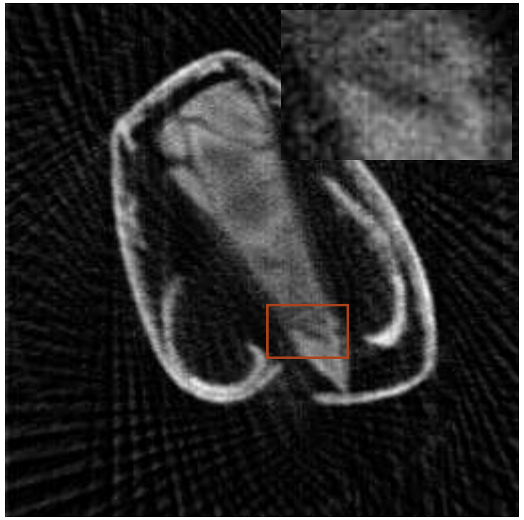
- ➢ Striping artifact and radiating artifact.
- ➢ Loss fine details and.
- ➢ Low level quality image.



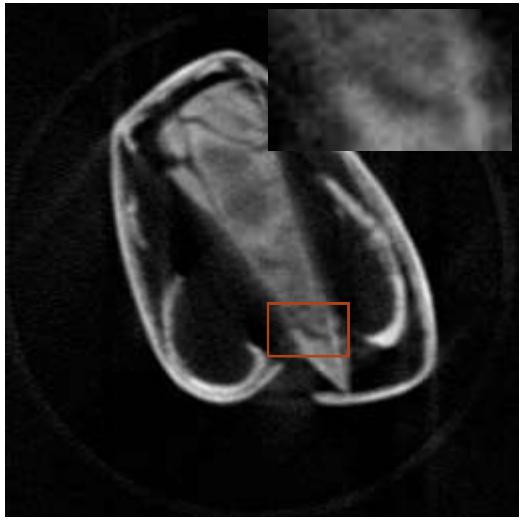
X-ray CT sparse-view reconstruction image



Groudtruth



Neutron CT sparse view reconstruction image



Groudtruth

02.

Target

Target

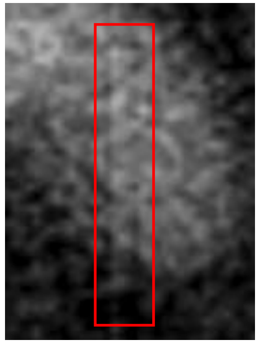
■ Key post-processing requirements for sparse-view CT

- ➢ Keep fine details and features
- ➢ Remove striping artifact
- ➢ Strong robustness

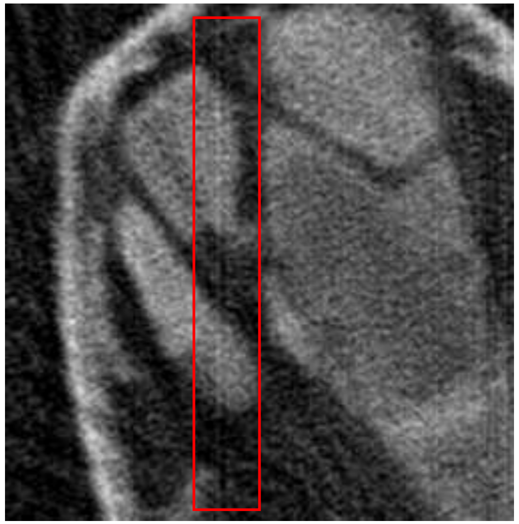
■ Deep learning denoising models are dominant

- ➢ Blind denoising, fast speed, good effects, strong adaptability
- ➢ Tradeoff between denoising and detail preservation, Control denoising strength, collect labelled training data
- ➢ More research on low-dose X-ray CT image denoising (medical imaging), less on neutron CT images

Learn local and global context in sparse-view CT image



Artifact or not ?

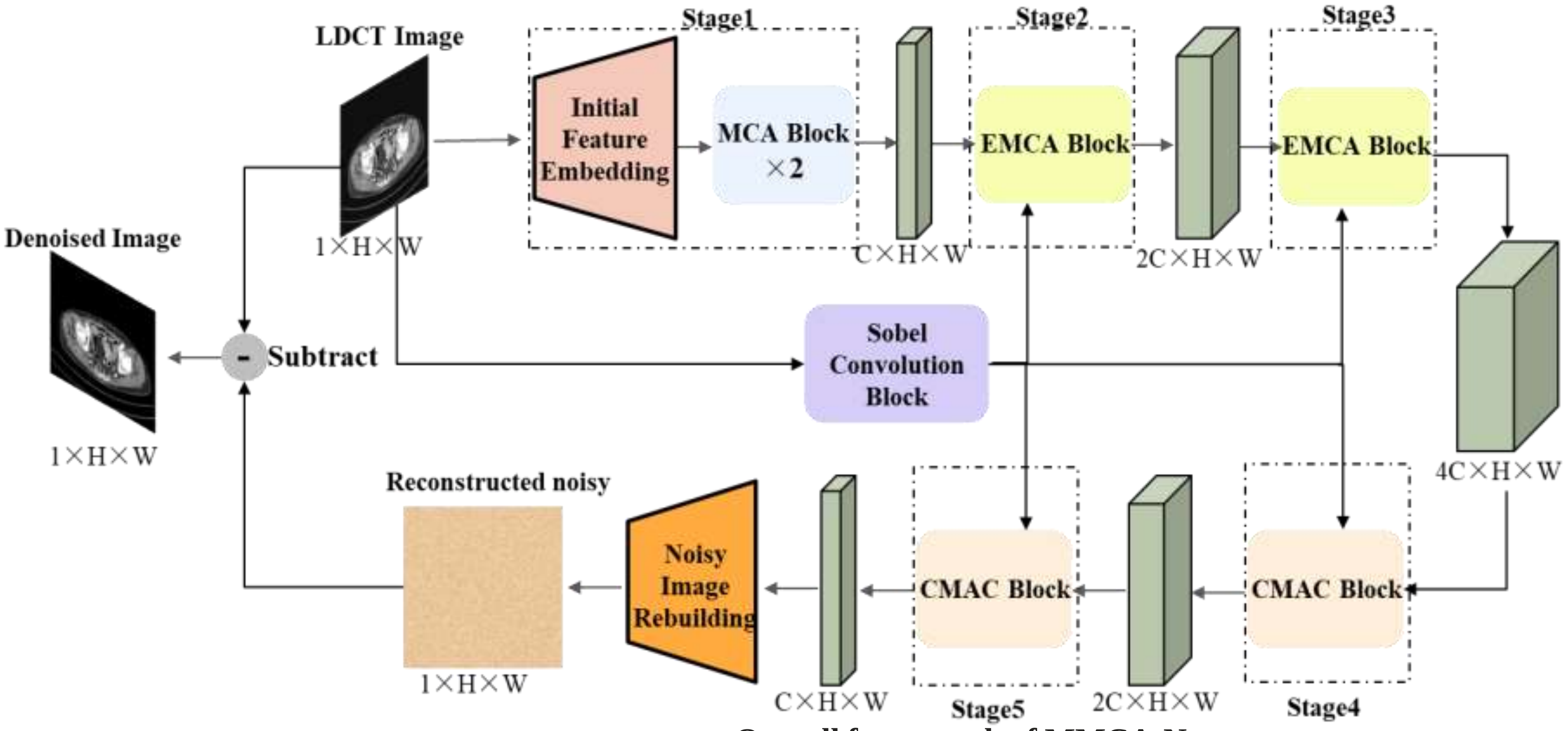


03. Method

Method

➢ The EMCA blocks explore context within the multi-order feature maps with channel dimension expansion.

➢ The CMCA blocks explore context within the multi-order feature maps with channel dimension compression.



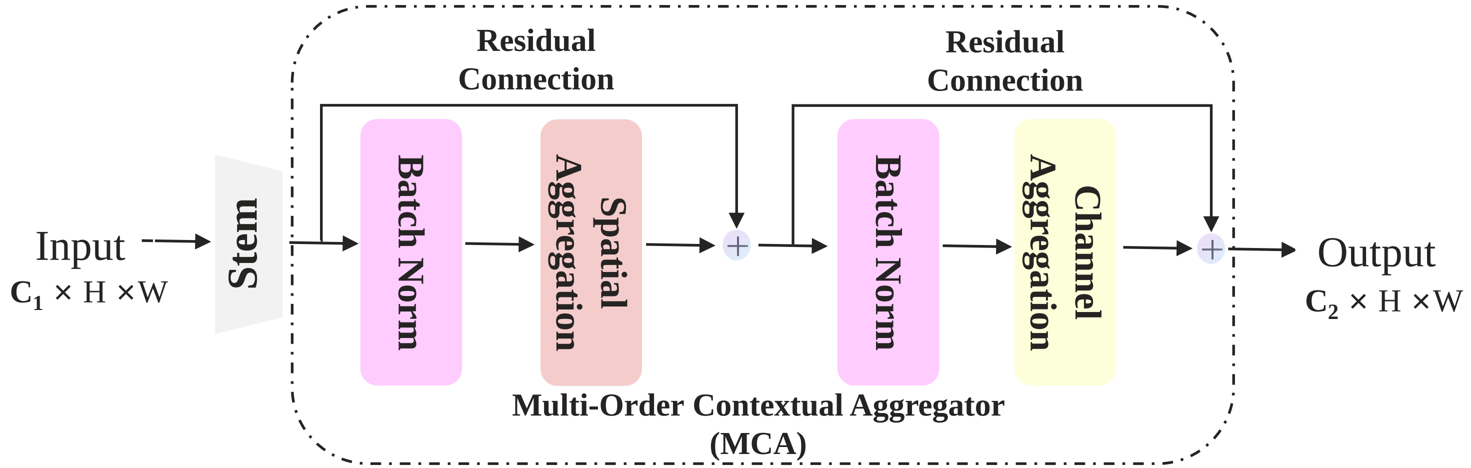
Overall framework of MMCA-Net

■ Characterize of designed MMCA-Net

➢ Employ multiple stages of multi-order context aggregation to capture contextual semantic relationships at various levels.

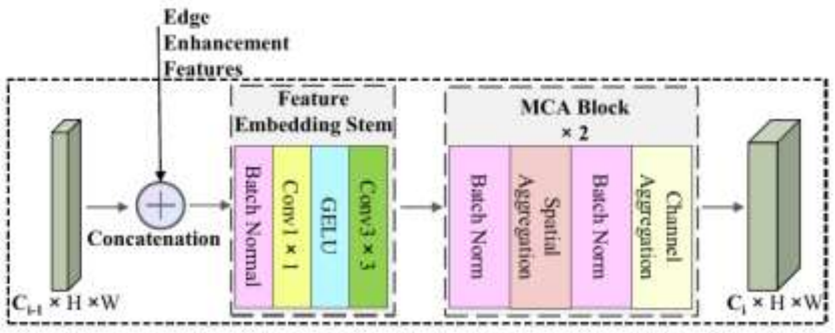
➢ Integrate four strategies to preserve detail information in the images.

Method

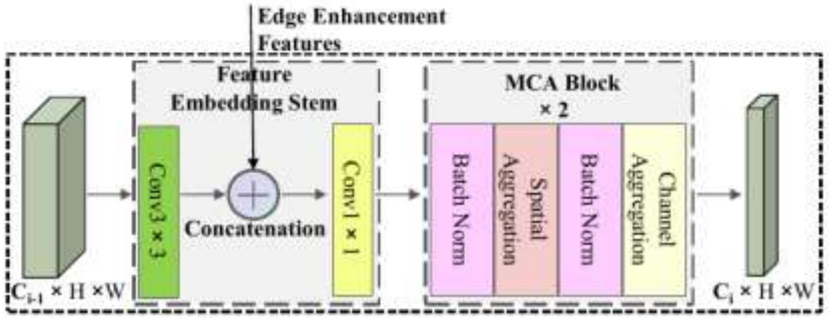


Macro architecture for each Stage

- ➢ Feature embedding stem generates contextual feature maps
- ➢ The MCA block is responsible for contextual feature extraction and aggregation.



EMCA



CMCA

04.

Experiment and Results Analysis

Experiment and Results Analysis

■ X-ray Low-Dose CT Dataset (LDCT Denoise):

- **AAPM-Mayo Clinic Low-Dose CT Grand Challenge dataset， 2167 training pairs (CT slices from 9 patients), 211 test pairs (1 patient).**
- **Quantitative metrics: PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index), and RSME (Root Mean Square Error).**

■ Sparse-view neutron/X-ray CT image datasets

- **X-ray sparse-view CT dataset：2048 pairs total，scanned object is metal.**
- **Neutron sparse-view CT dataset：2048 pairs total，scanned object is cultural relic.**

Experiment and Results Analysis

■ X-ray low dose CT image denoise（LDCT denoise）

Methods	PSNR↑	SSIM↑	RMSE↓	Parameters	Running times
LDCT	29.2489 ± 2.1100	0.8759 ± 0.0386	14.2416 ± 3.9523	\	\
BM3D(2014) [25]	32.6911 ± 2.0693	0.9046 ± 0.0302	9.5730 ± 2.6503	\	2.3220s
REDCNN(2017) [11]	32.9012 ± 1.6609	0.9086 ± 0.0283	9.2354 ± 1.9518	1.8456M	**0.0022s**
EDCNN(2020) [13]	33.0571 ± 1.8456	0.9146 ± 0.0289	9.1158 ± 2.1848	**0.0810M**	0.0031s
DUGAN(2021) [18]	32.8442 ± 1.8621	0.9056 ± 0.0278	9.6898 ± 2.3891	\	0.0224s
CTformer(2023) [31]	33.0811 ± 1.7688	0.9119 ± 0.0304	9.6898 ± 2.0549	1.4500M	0.4414s
DEformer(2022) [34]	33.0655 ± 1.8790	0.9151 ± 0.0290	9.1142 ± 2.2290	0.3547M	0.0713s
ESAU-Net(2023) [52]	33.2593 ± 1.8079	**0.9174 ± 0.0284**	8.8961 ± 2.0722	4.9140M	0.0207s
MMCA-S(Ours)	33.2649 ± 1.7875	0.9157 ± 0.0294	8.8854 ± 2.0409	0.5710M	0.0216s
MMCA(Ours)	**33.4418 ± 1.7997**	0.9165 ± 0.0294	**8.8095 ± 2.0346**	0.9300M	0.0200s

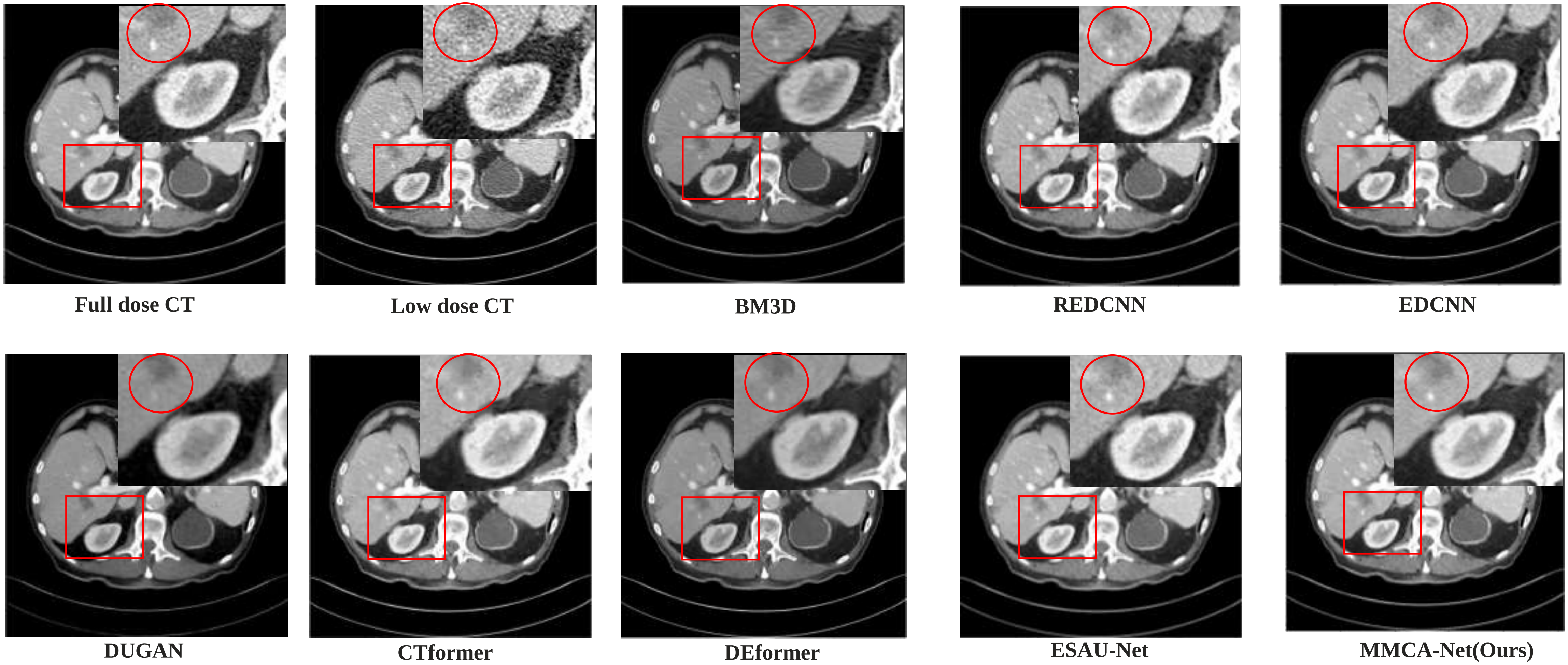
Quantitative comparison results with other advanced methods of recent years

PSNR: 1st place,   SSIM: 2st place, RMSE: 1st place.

Parameters:3st place,   Average running time:3st place.

Experiment and Results Analysis

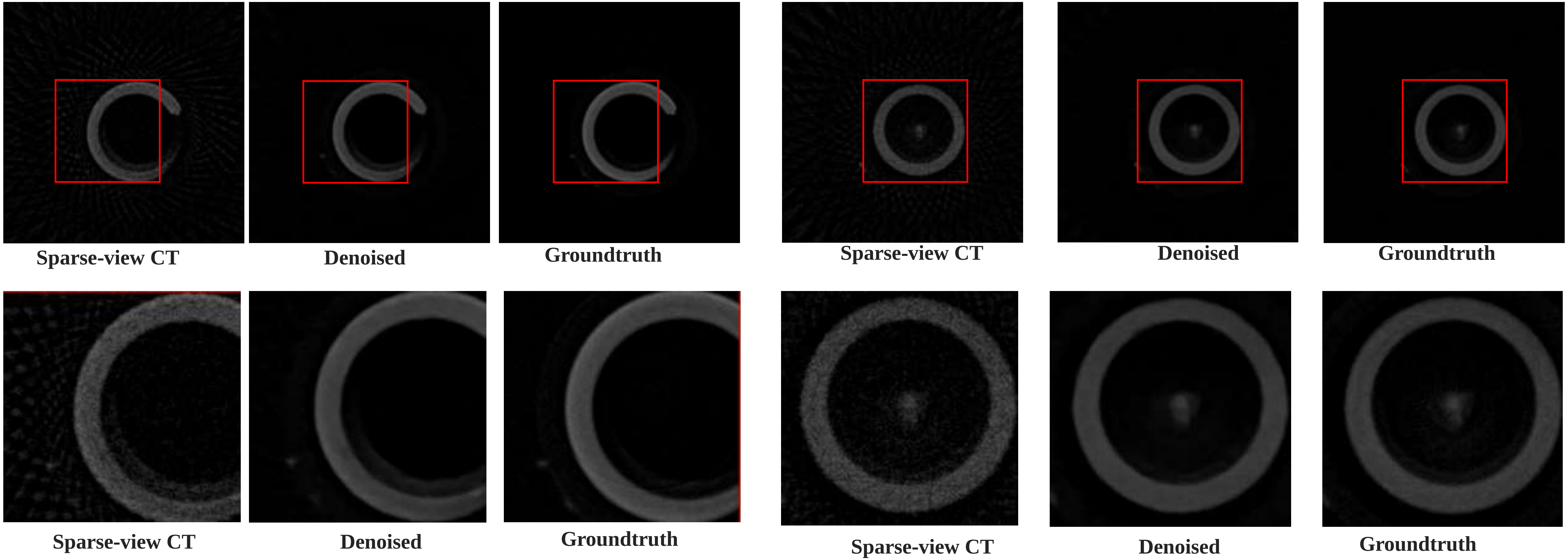
■ X-ray low dose CT image denoising (LDCT denoising)



Visualization[-160, 240]HU

Experiment and Results Analysis

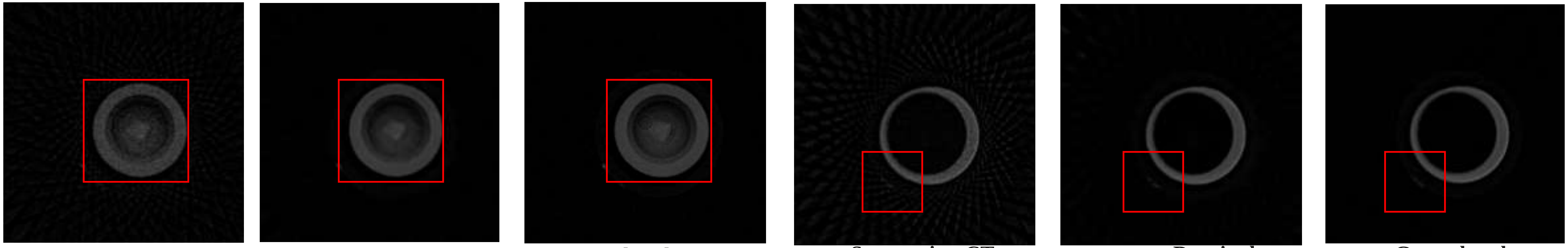
■ X-ray sparse-view CT image denoising



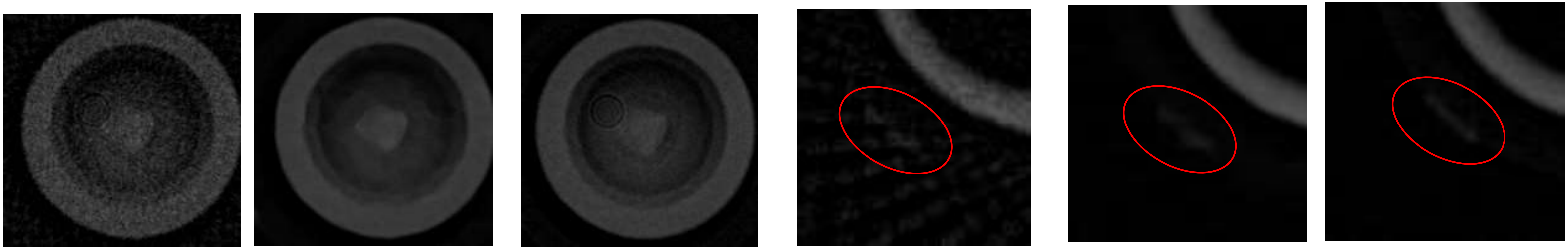
- Only trained on x-ray sparse-view CT dataset.
- Successfully improve the image quality by removing noise and strip artifacts

Experiment and Results Analysis

■ X-ray sparse-view CT image denoising



Sparse-view CT | Denoised | Groundtruth | Sparse-view CT | Denoised | Groundtruth

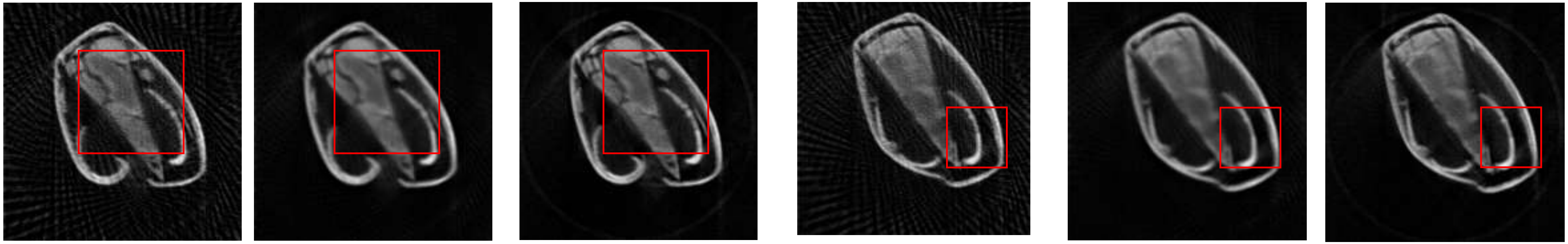


Sparse-view CT | Denoised | Groundtruth | Sparse-view CT | Denoised | Groundtruth

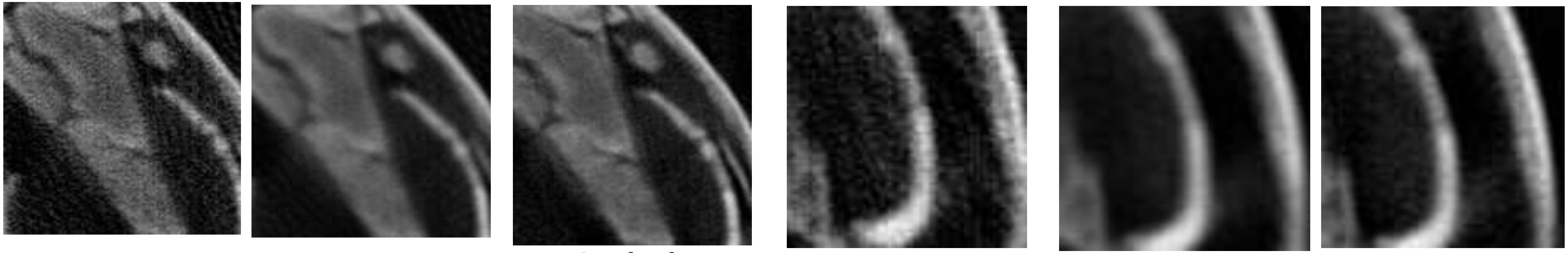
- ➢ the contrast change is not natural.
- ➢ Some details are not perfectly preserved

Experiment and Results Analysis

Neutron sparse-view CT image denoising



Sparse-view CT | Denoised | Groudtruth | Sparse-view CT | Denoised | Groudtruth



Sparse-view CT | Denoised | Groudtruth | Sparse-view CT | Denoised | Groudtruth

- Trained on the dataset mixed with X sparse-view CT image dataset.
- Successfully improve the image quality by removing noise and strip artifacts.

05.

Conclusion and outlook

Conclusion and outlook

Conclusion

- We designed a deep learning denoising model that is capable of awaring both local and global contexts. The test results on public dataset show the excellent performance compared to the state-of-the-art methods.
- We applied the designed network model to remove noise and artifacts from neutron/X-ray sparse-view CT images and achieved notable improvements in image quality.

Limitations and outlook

- The denoising process is low interpretable. The impact of denoising on the original fine details is uncertain.
- In the future, we will combine sparse-view reconstruction methods to further enhance the quality of CT images.


THANK YOU
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