Neural Network Based Metal Artifact Reduction

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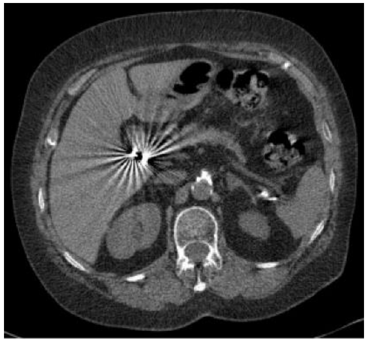
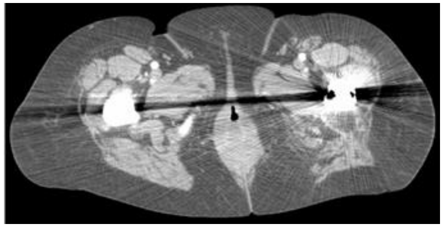
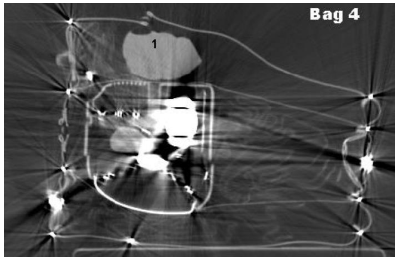
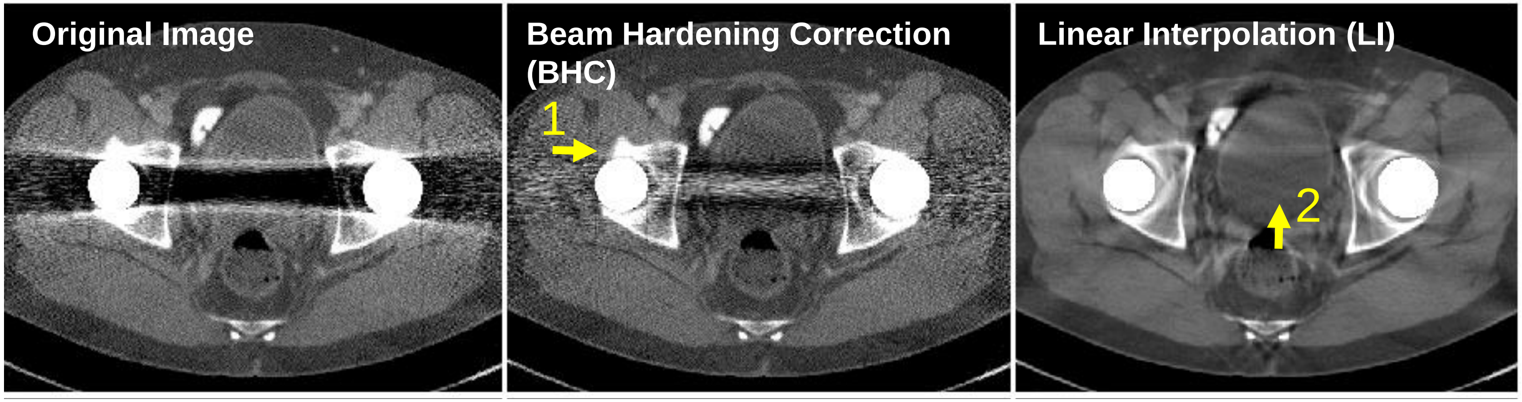
Metal Artifacts

- Metal:
  - Clinical: dental fillings, hip prostheses, surgical clips, ...
  - Security: metallic objects in luggage
- Artifacts:
  - Clinical: poor image quality, low confidence for diagnosis
  - Security: obstacles for target recognition
- Reason: beam hardening, noise, scatter,...
- Complexity: different metal sizes, positions, materials
- Methods: data correction, data replacement, iterative reconstruction
- Idea: reduce artifacts using deep neural network.

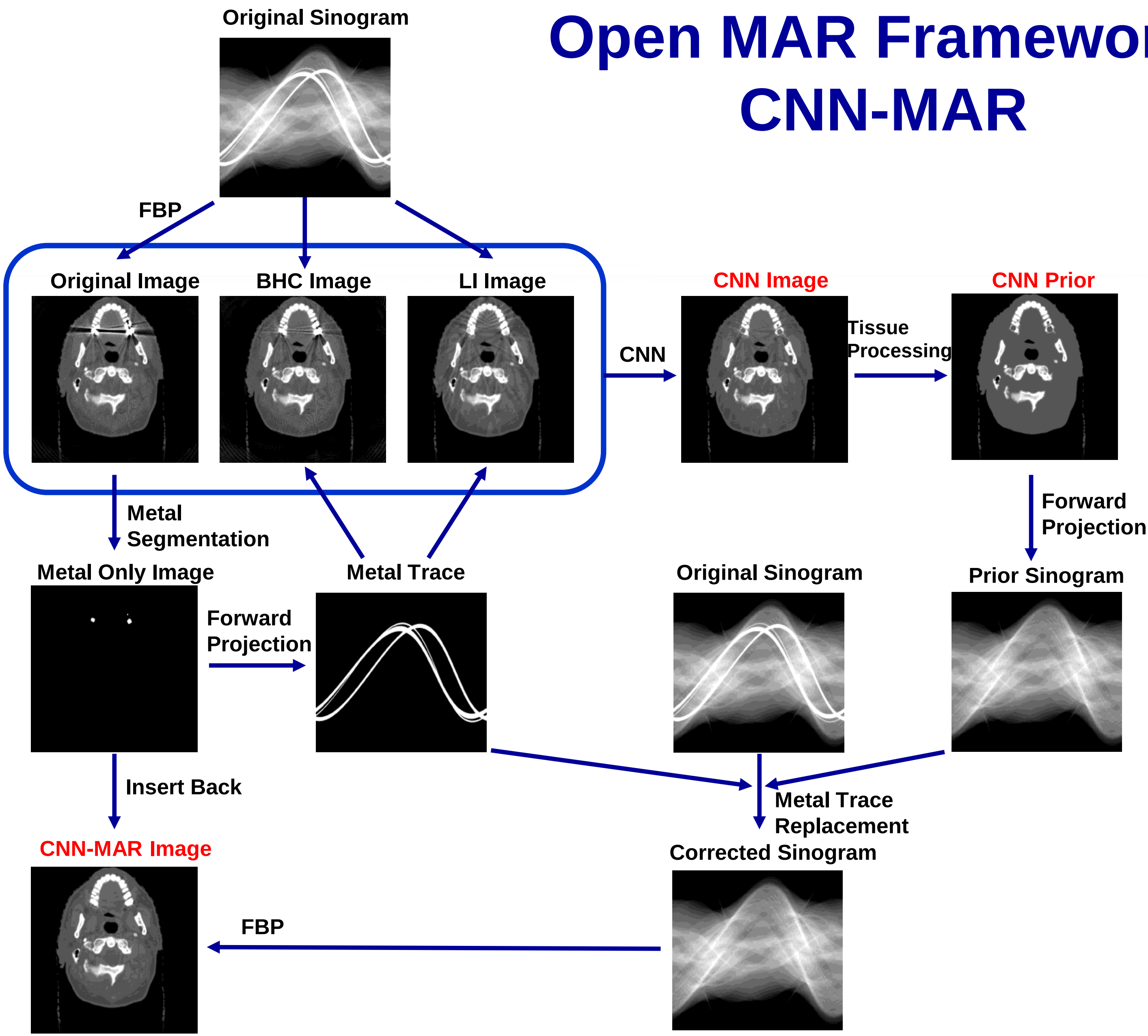
Open MAR framework

- Key: Fuse complementary information provided by different methods
- Advantages:
  - Open framework: incorporate various MAR methods
  - Outstanding performance: restore anatomical structures
  - Data-driven: robust



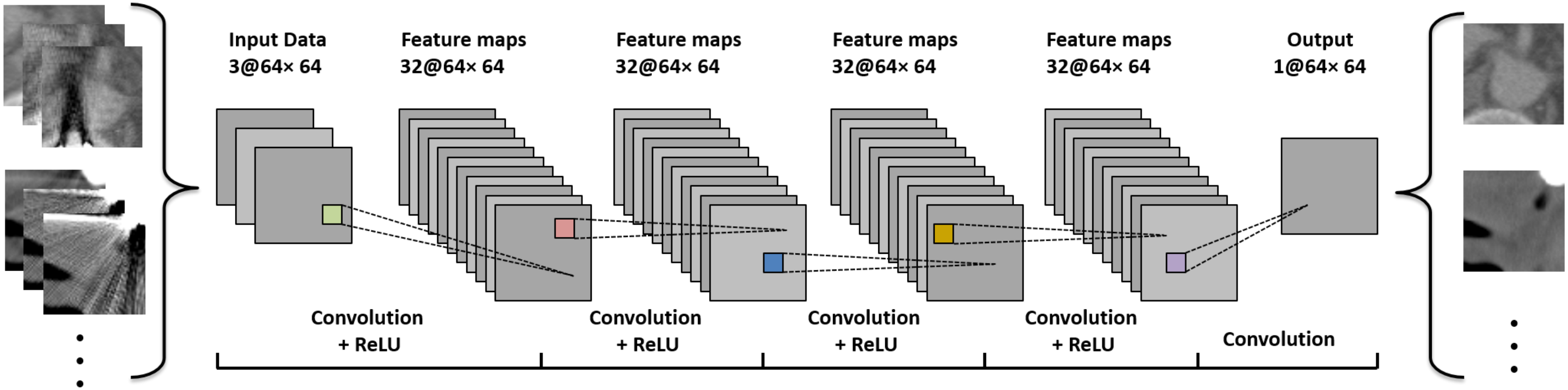
[1] Y. Zhang, Y. Chu, and H. Yu, "Reduction of metal artifacts in x-ray CT images using a convolutional neural network," in *SPIE Optical Engineering + Applications*, August 2017.
[2] Zhang, Yanbo, and Hengyong Yu. "Convolutional Neural Network based Metal Artifact Reduction in X-ray Computed Tomography." *IEEE Transactions on Medical Imaging* (2018).

Open MAR Framework: CNN-MAR



Convolutional Neural Network (CNN)

- Input: the original, BHC and LI image patches (64×64×3)
- Target: reference image patches (64×64×1)
- Convolutional kernel: 3×3
- Padding: 1
- ReLU



Architechture of the convolutional neural network for metal artifact reduction.

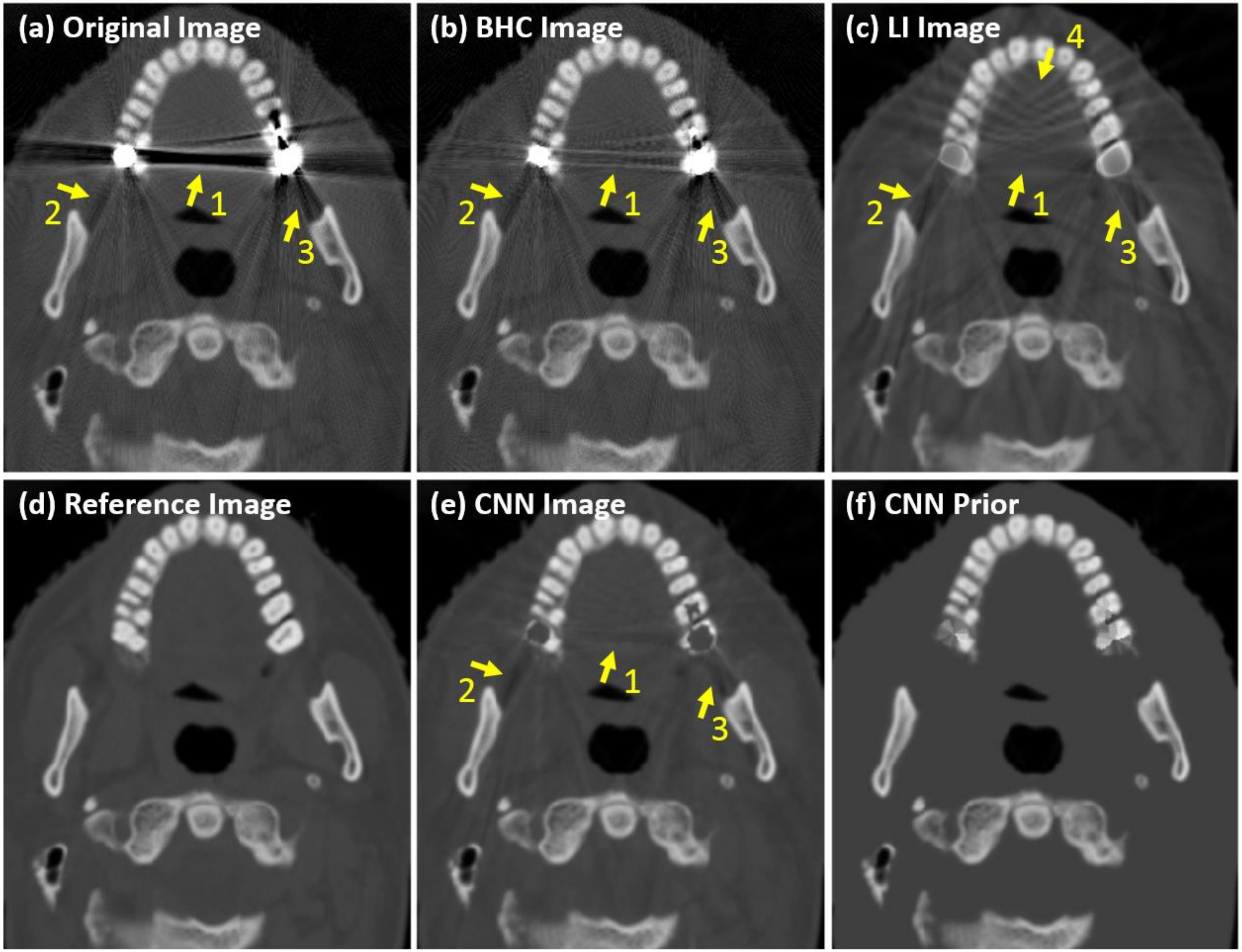
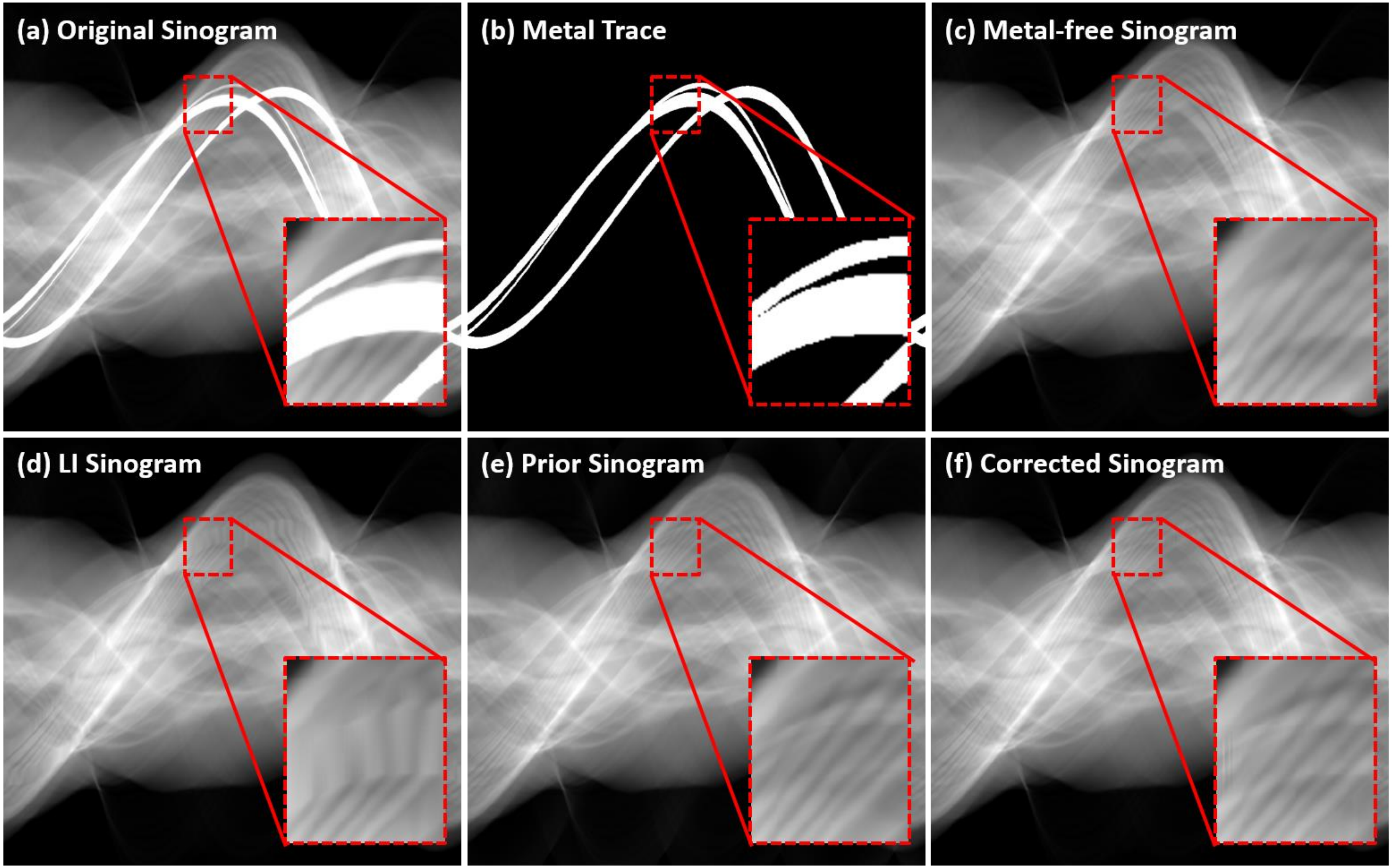
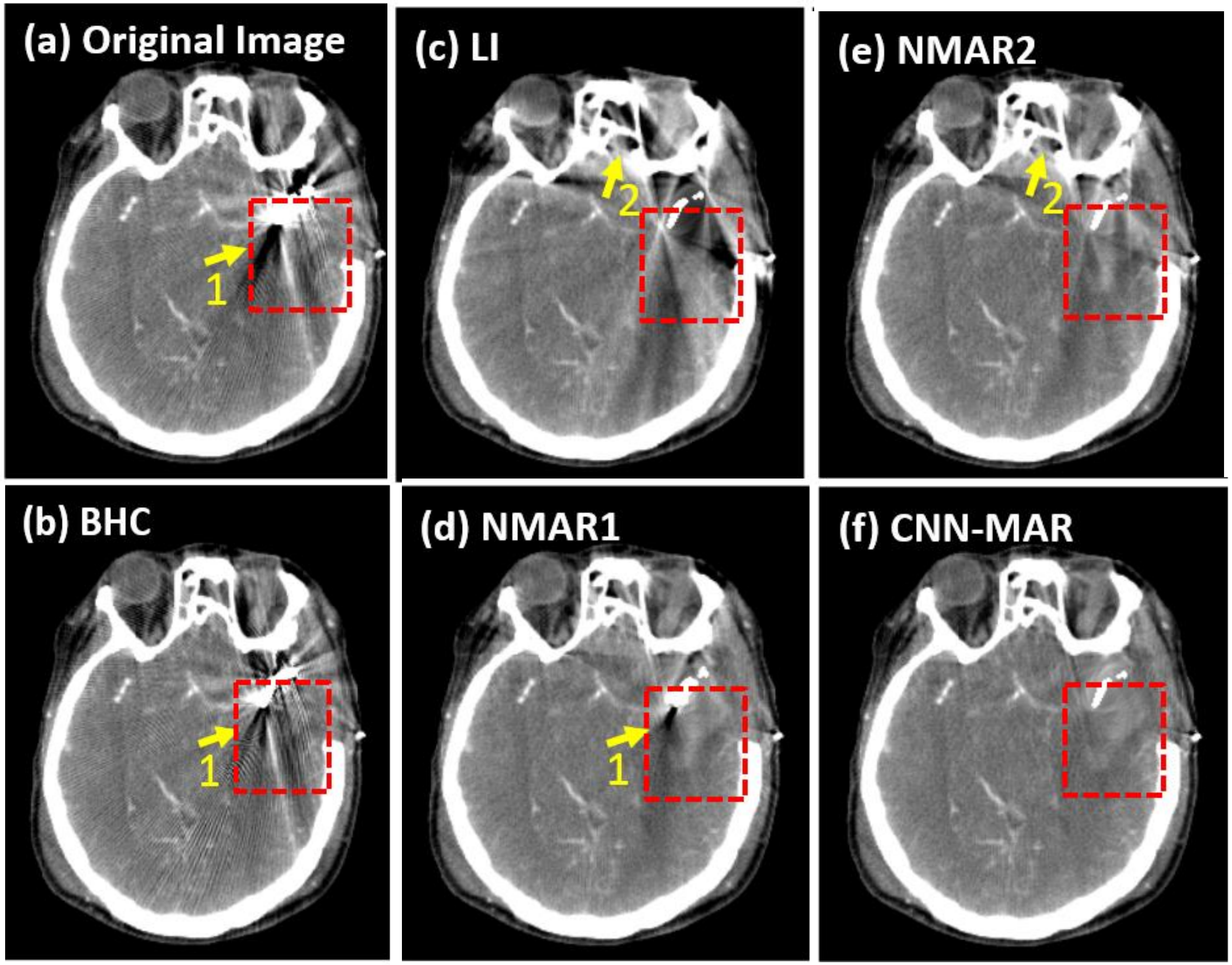


Illustration of the CNN image and prior.



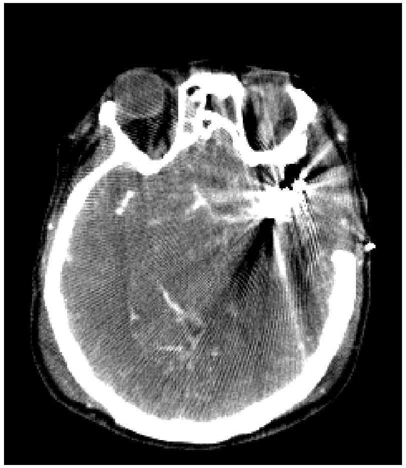
Comparison of sinogram completion. An ROI is enlarged and displayed with a narrower window.

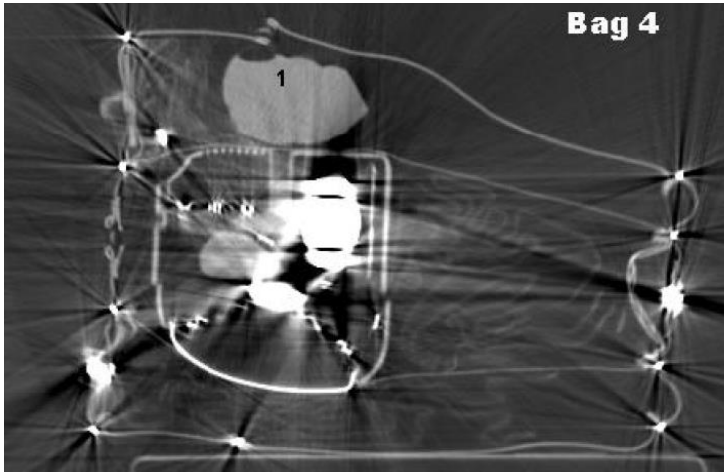
Clinical Data



A 59 year-old female with diffused subarachnoid hemorrhage (highlighted by the red square). CT angiography demonstrated a left middle cerebral artery aneurysm, which was clipped. The display window is [-100 200] HU.

Clinical data *v.s* Security data





Karimi, Seemeen, et al. "Metal artifact reduction for CT-based luggage screening." *Journal of X-ray science and technology,* 2015.

Metal:	Small, single material	Large, multiple materials (limitation: 1^{st} order BHC)
Background:	Soft tissue, bone	Multiple materials (limitation: tissue processing)
Purpose:	Precise attenuation coefficients	Target recognition (Easier)

Limitations and Future Work

1. Deep learning based metal segmentation

- Advantage: Semantic segmentation
- Metal segmentation: Deep learning can segment out metal implants more precisely

2. Apply advanced model (e.g., ResNet, GAN)

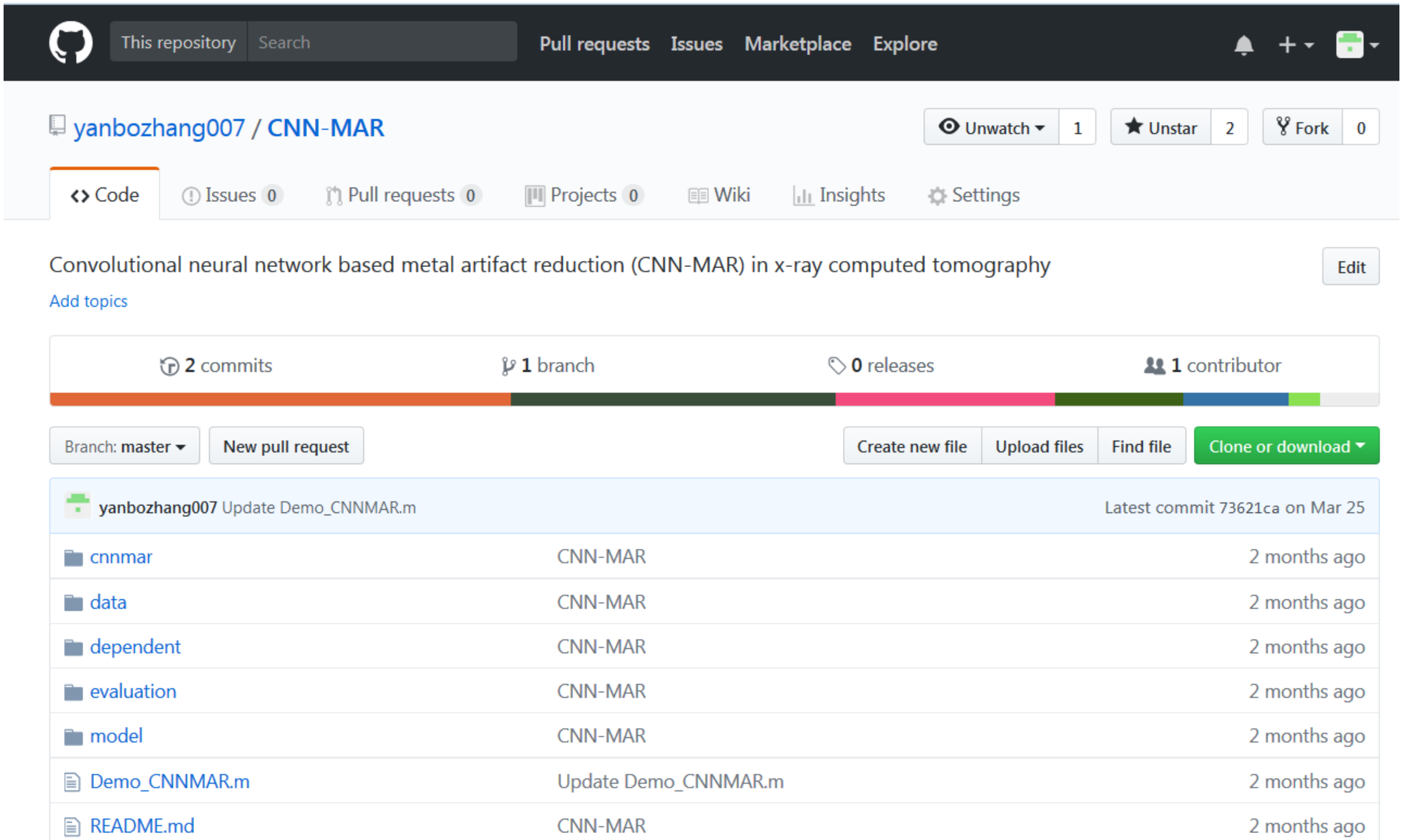
- Advantage: A more powerful CNN model
- Distinguish metal artifacts from anatomical structures better.

3. Other artifacts

- Beam hardening, scattering, motion artifacts, etc.

Open Source Code

https://github.com/yanbozhang007/CNN-MAR

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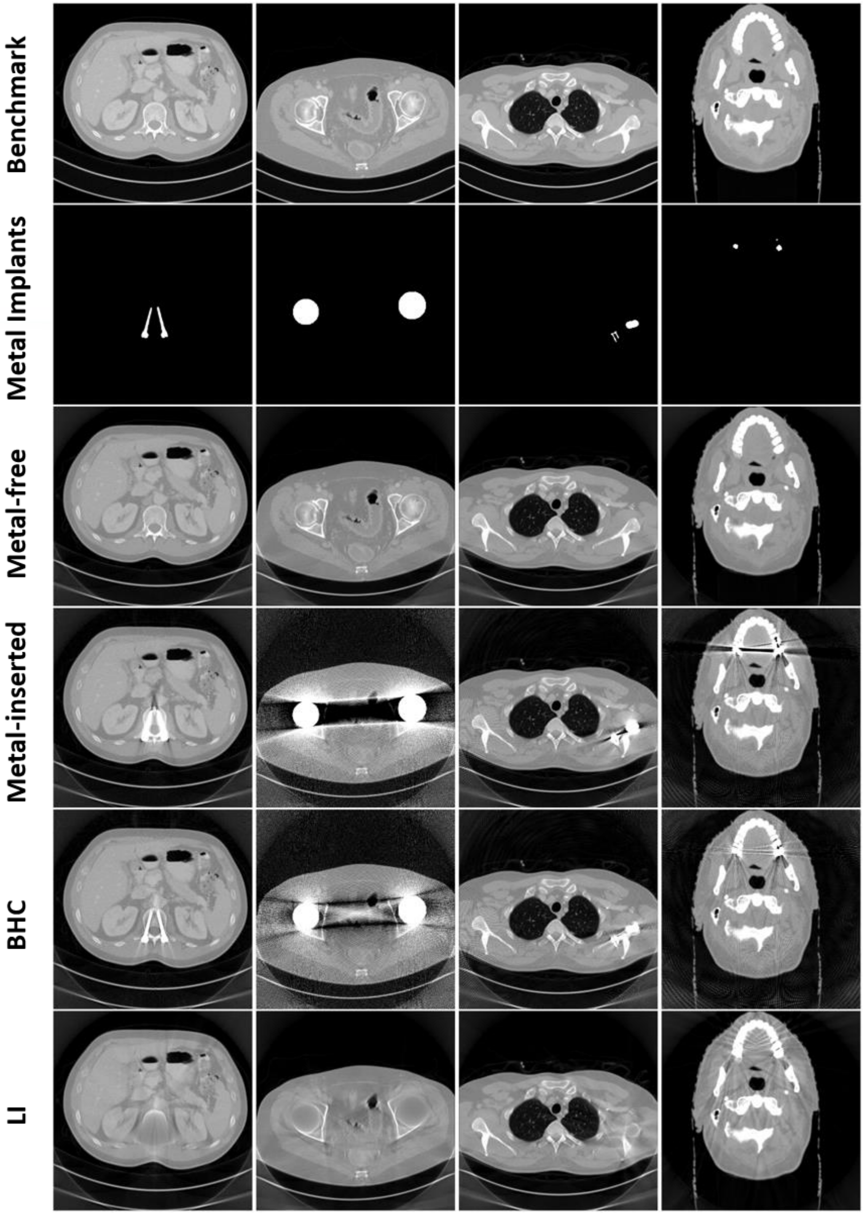
Thank You !

Backup Slides

Experiments

Build a Metal Artifacts Database

- 74 DICOM images
- 15 metal shapes
- 100 cases
- Metal-free, metal-inserted, BHC and LI corrected images
- Equi-angular fan-beam
- 120 kVp
- Beam hardening and Poisson noise



Experiments

Numerical Simulation

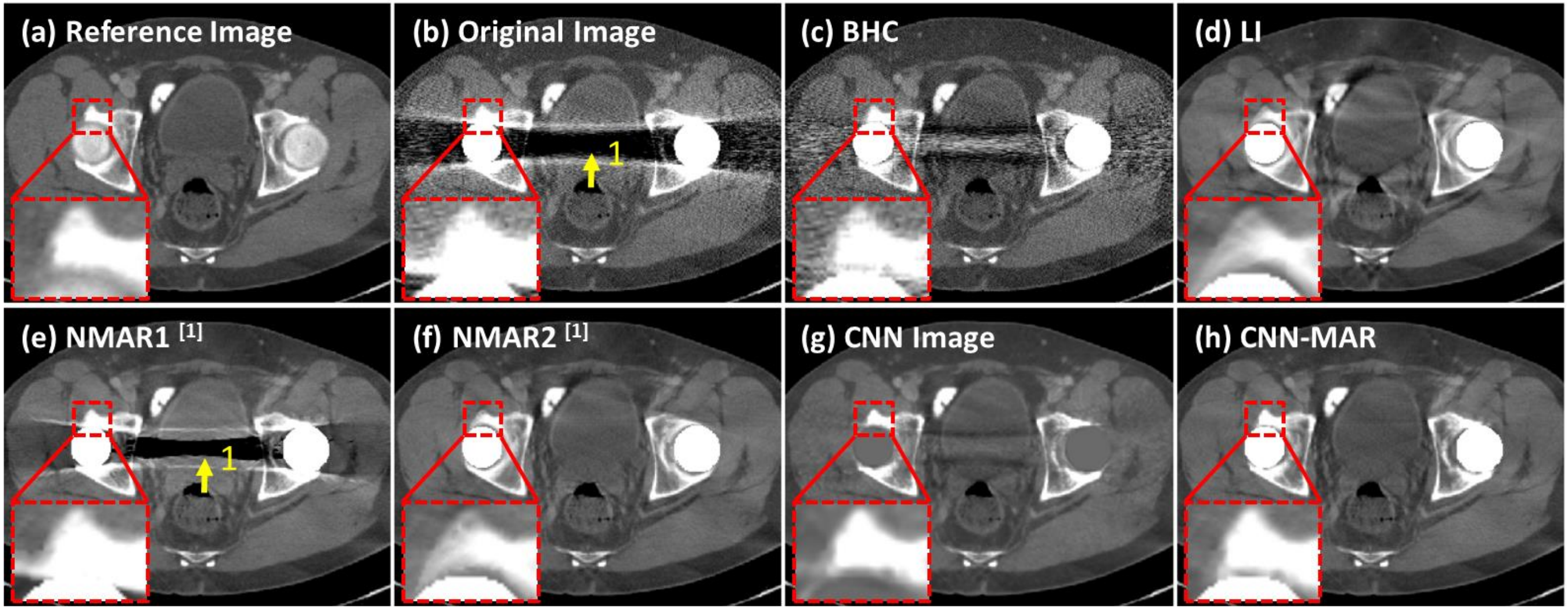
- Case 1: hip prostheses
- Case 2: fixation screws
- Case 3: dental fillings
- Same simulation parameters to that of cases in the database

Real Data

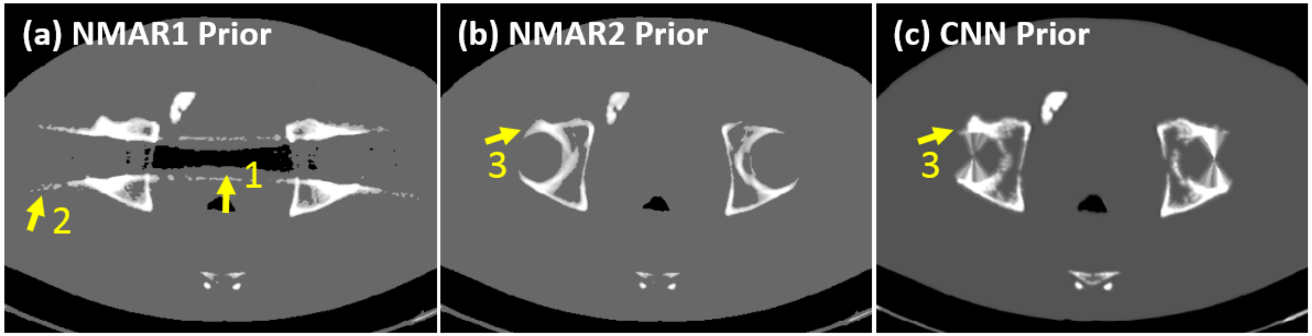
- A 59-year old female patient with a surgical clip
- Siemens SOMATOM Sensation 16 CT scanner
- 120 kVp and 496 mAs
- 1160 projection views per rotation
- 672 detector bins in a raw

Simulation

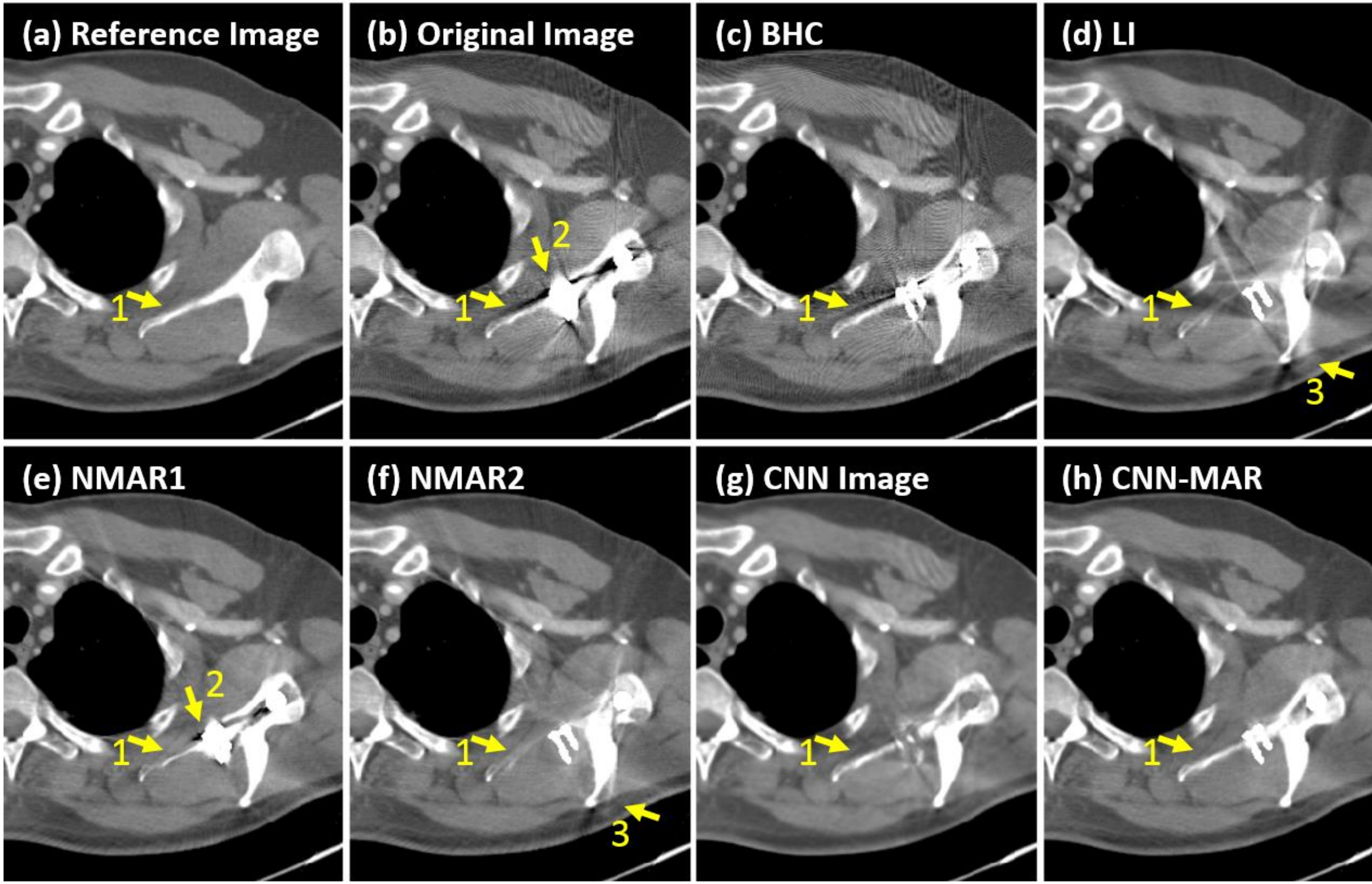
Case 1: bilateral hip prostheses.



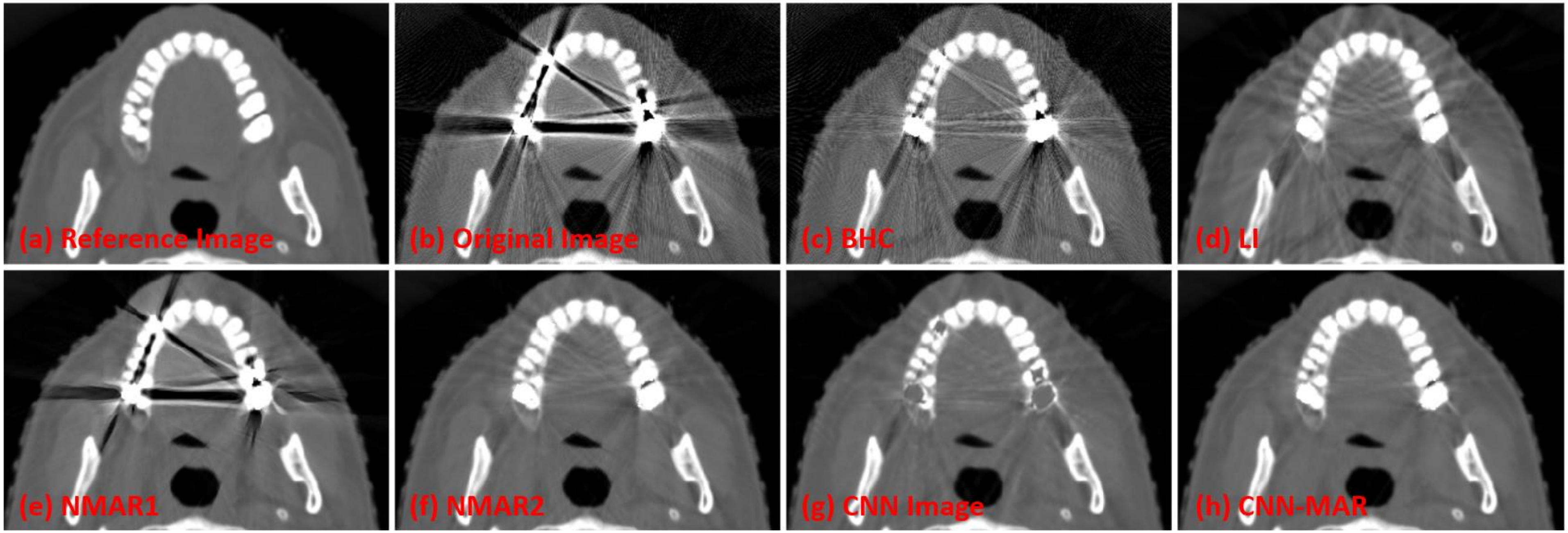
Prior images:



[1] E. Meyer *et al.*, "Normalized metal artifact reduction (NMAR) in computed tomography," *Medical Physics*, 2010.



Case 2: two fixation screws and a metal inserted in the shoulder blade.



Case 3: four dental fillings.

Table I. RMSE of each image in the numerical simulation study. (Unit: HU).

	Original	BHC	LI	NMAR1	NMAR2	CNN	CNN-MAR
Case 1	155.0	86.3	46.2	121.2	35.4	33.1	29.1
Case 2	71.5	44.4	54.5	50.4	41.4	31.5	22.8
Case 3	320.3	183.5	107.3	234.9	82.3	83.4	58.4

Table II. SSIM of each image in the numerical simulation study.

	Original	BHC	LI	NMAR1	NMAR2	CNN	CNN-MAR
Case 1	0.565	0.576	0.930	0.887	0.935	0.940	0.943
Case 2	0.883	0.854	0.931	0.955	0.950	0.965	0.977
Case 3	0.522	0.536	0.886	0.833	0.942	0.932	0.967