Convolutional Neural Network based Metal Artifact Reduction in X-ray Computed Tomography

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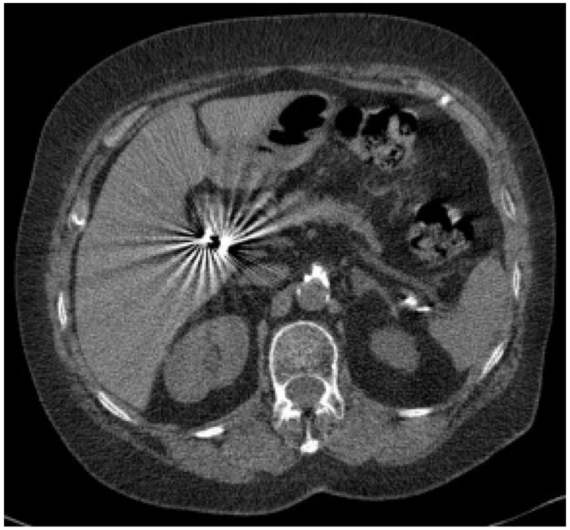
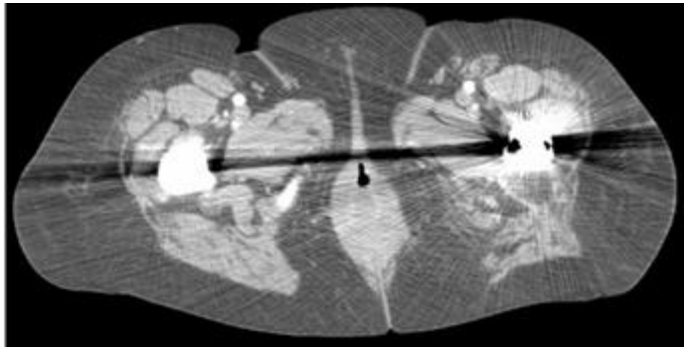
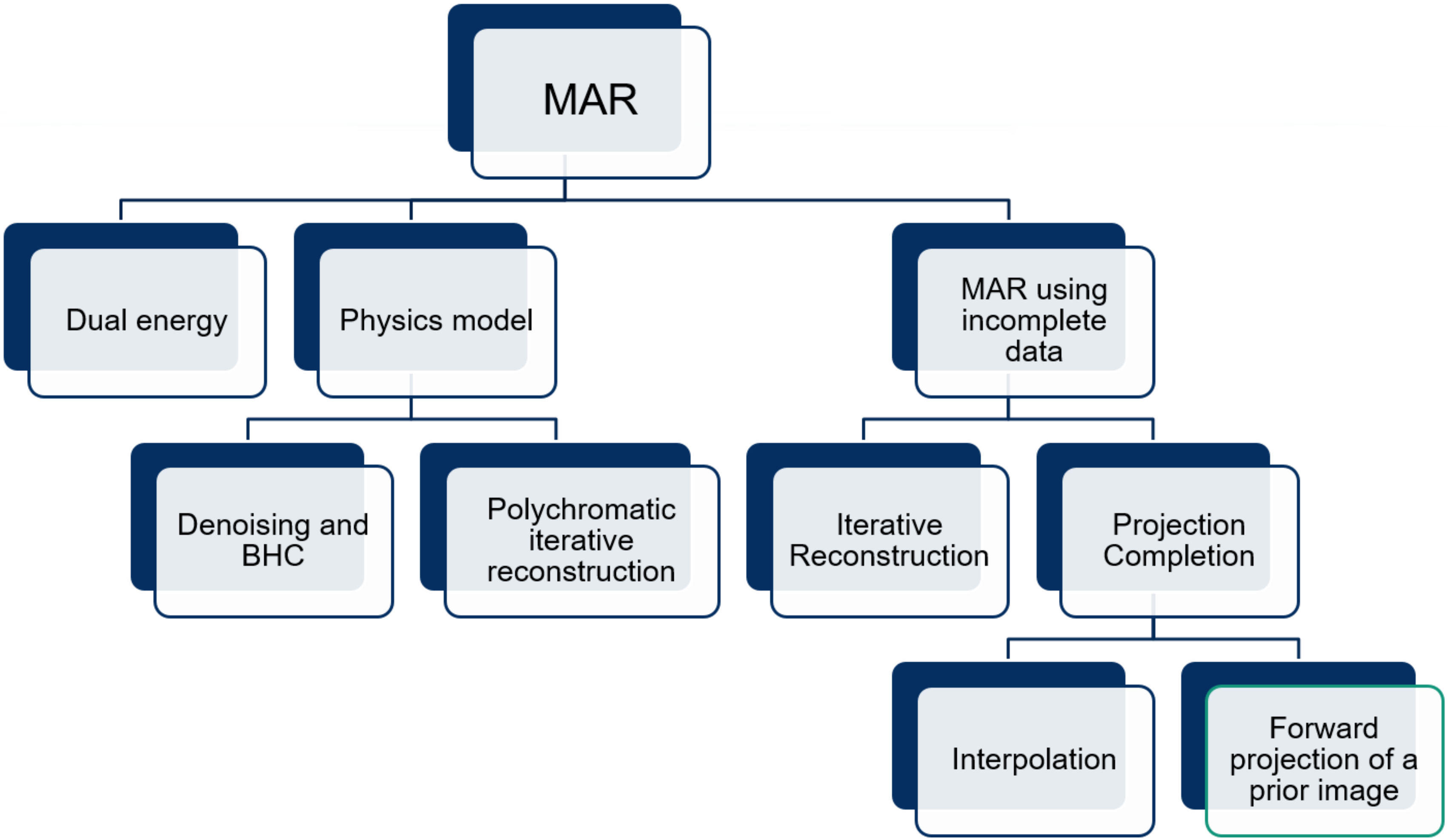
Metal Artifacts

- Dental fillings, hip prostheses, surgical clips, ...
- Beam hardening, noise, scatter,...



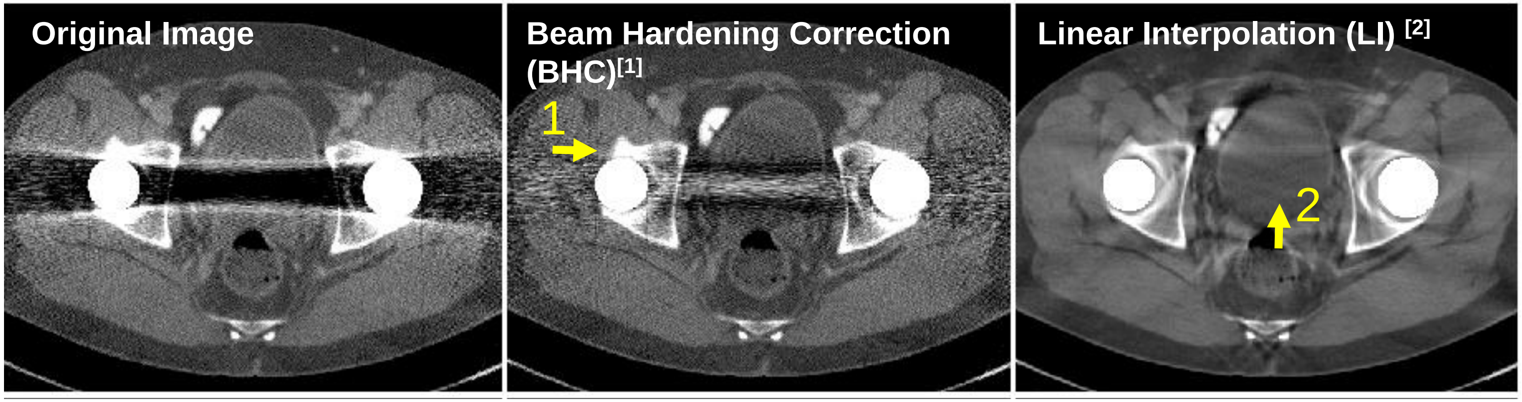


Metal Artifact Reduction (MAR)



Metal Artifact Reduction (MAR)

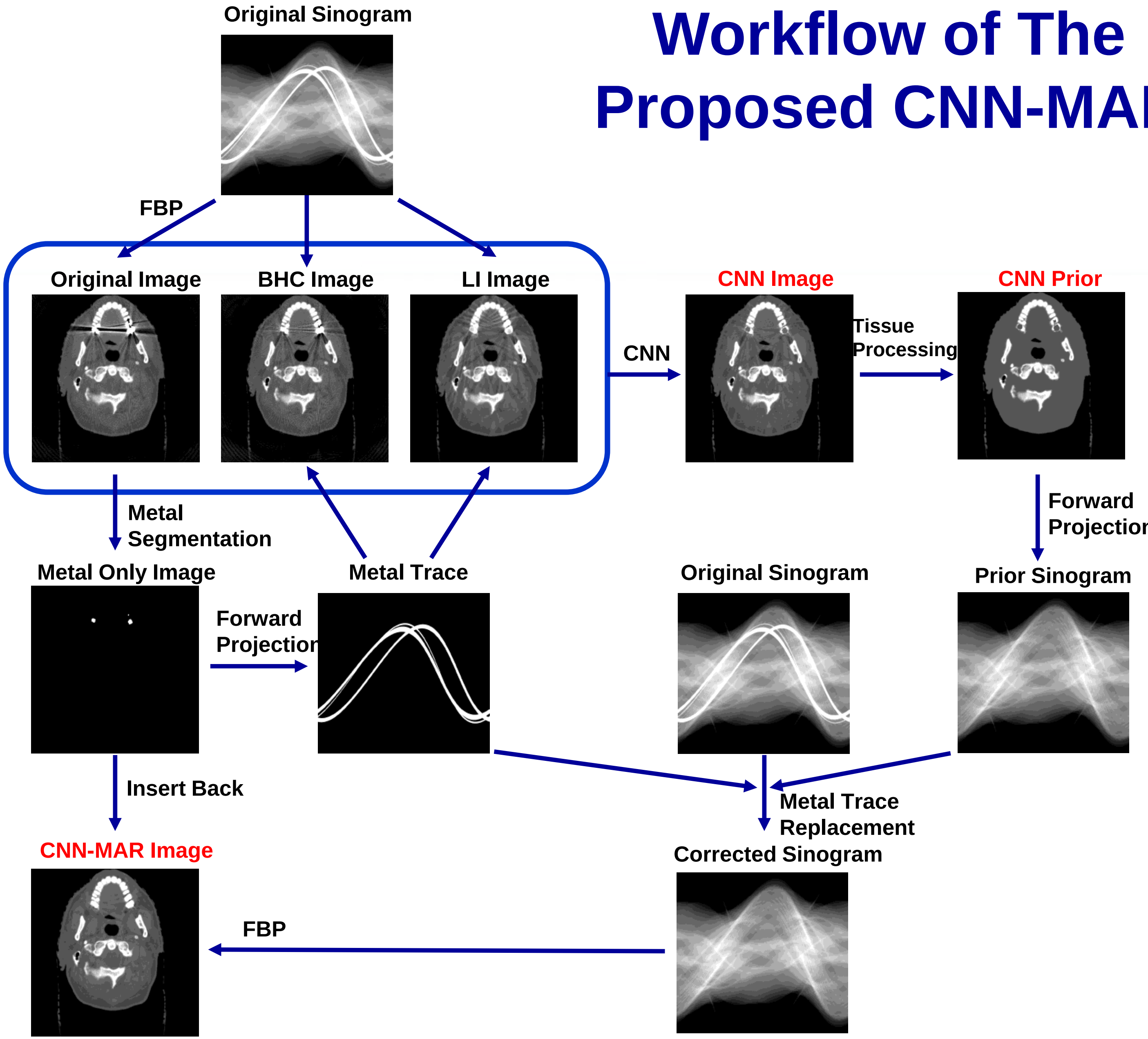
- No standard MAR methods
- Case-by-case
- *Complementary information*



[1] J. M. Verburg and J. Seco, "CT metal artifact reduction method correcting for beam hardening and missing projections," *Physics in Medicine and Biology*, vol. 57, pp. 2803-2818, 2012.

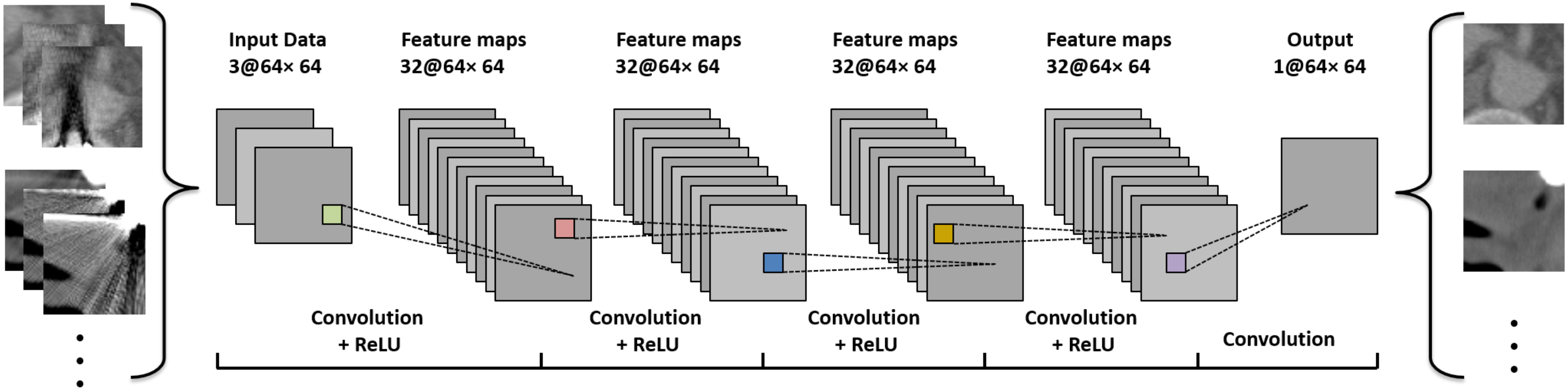
[2] W. Kalender, R. Hebel, and J. Ebersberger, "Reduction of CT artifacts caused by metallic implants," *Radiology*, vol. 164, p. 576, 1987.

Workflow of The Proposed 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



Configuration of the convolutional neural network for metal artifact reduction.

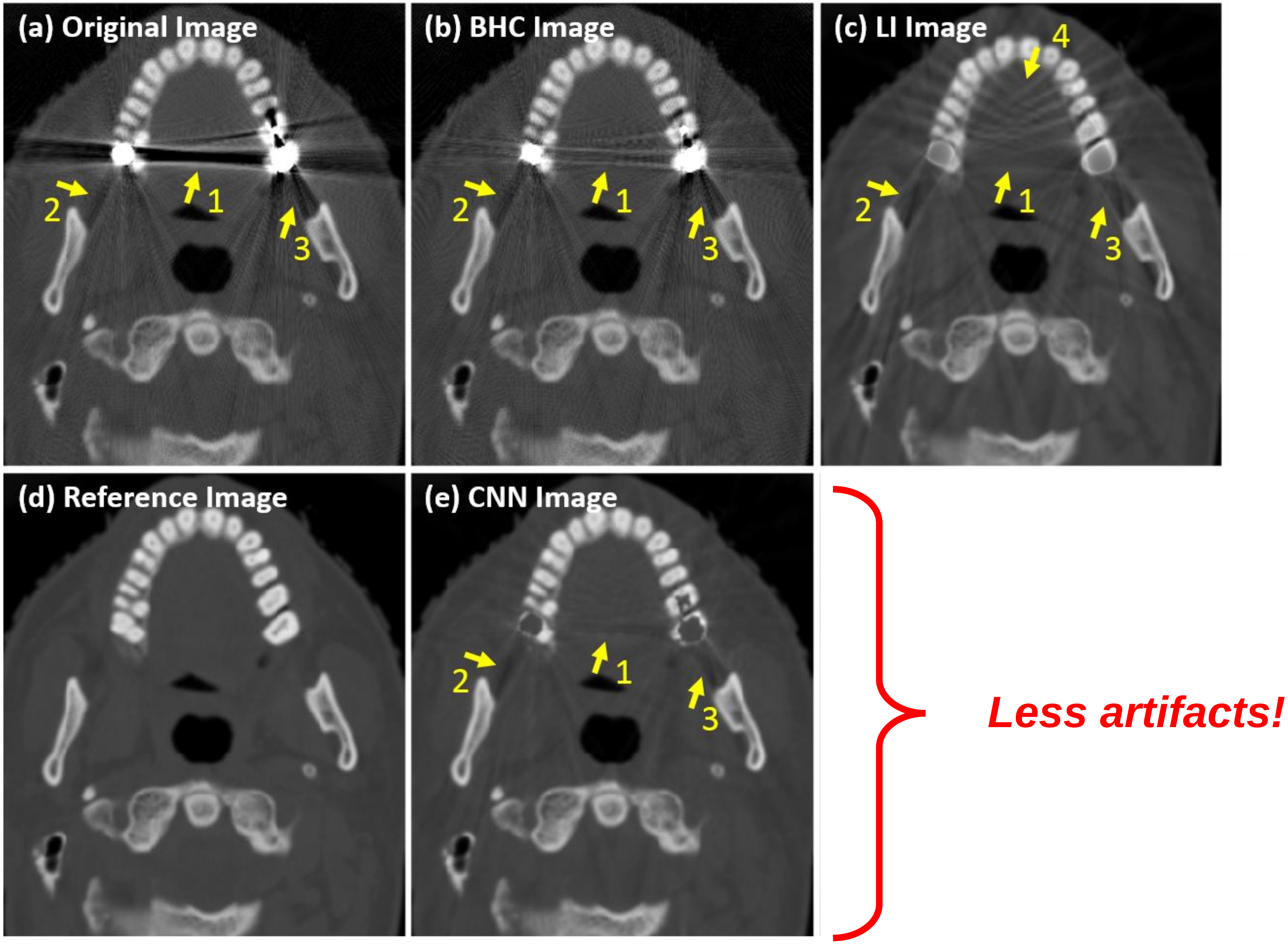
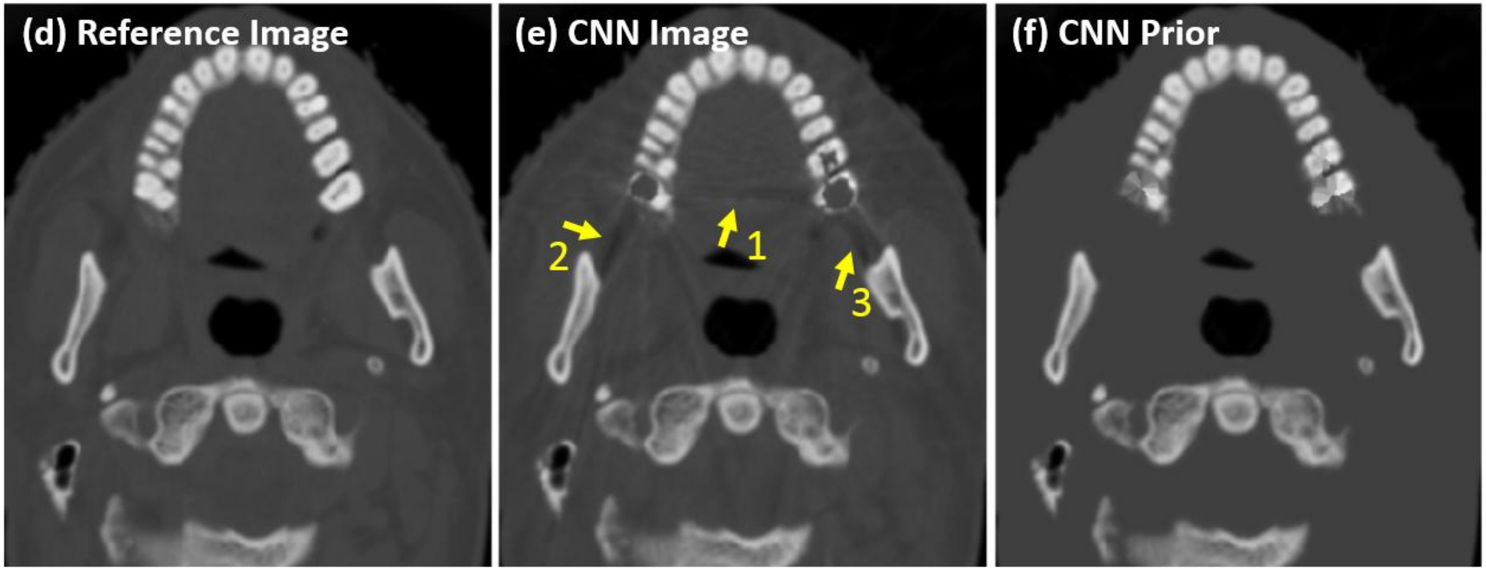
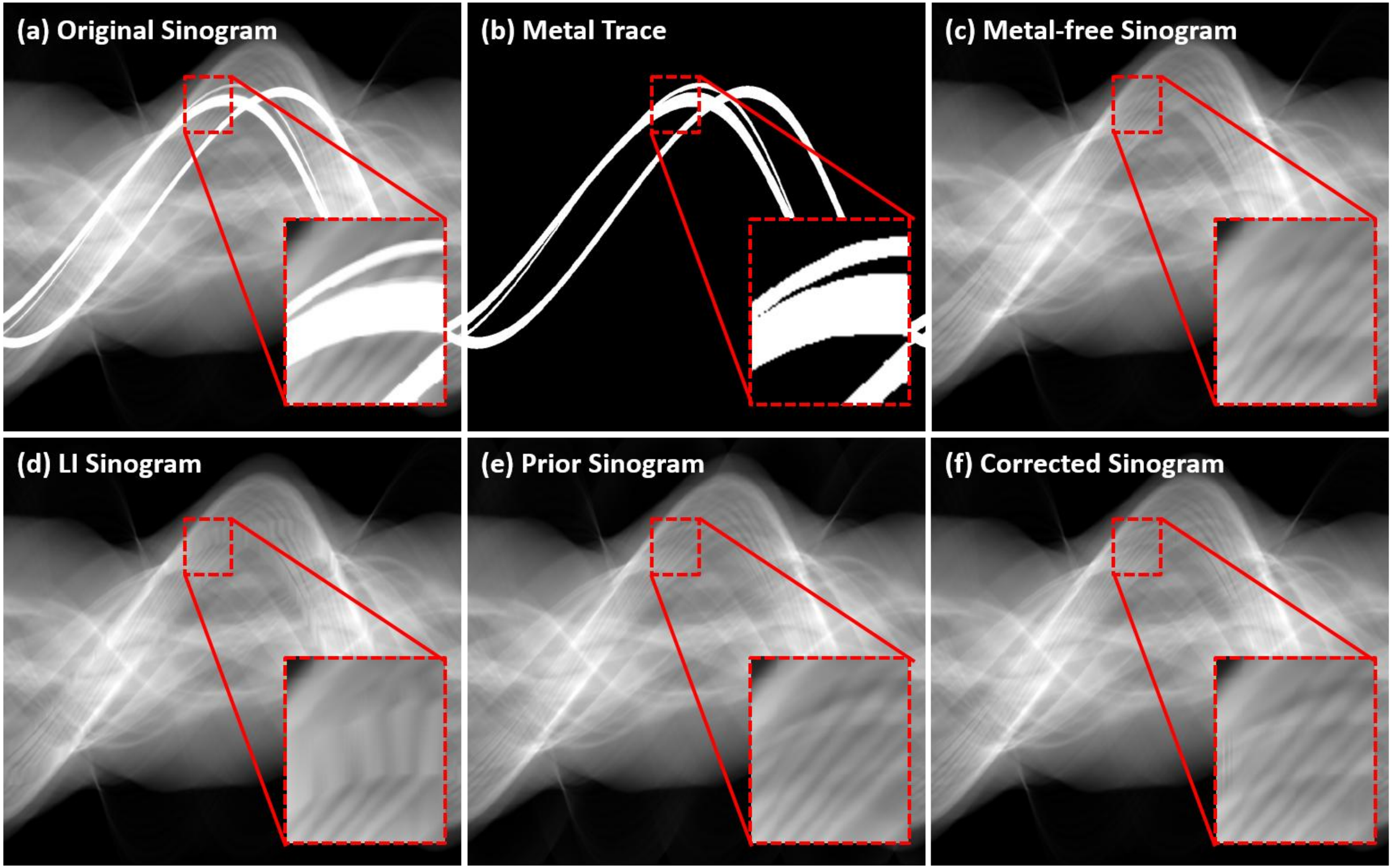


Illustration of the CNN image.

Tissue Processing

- The CNN image: Residual artifacts
- Thresholding based segmentation (k-means):
  - Bone
  - Soft tissue
  - Air
- Soft tissue: set to a uniformed value.



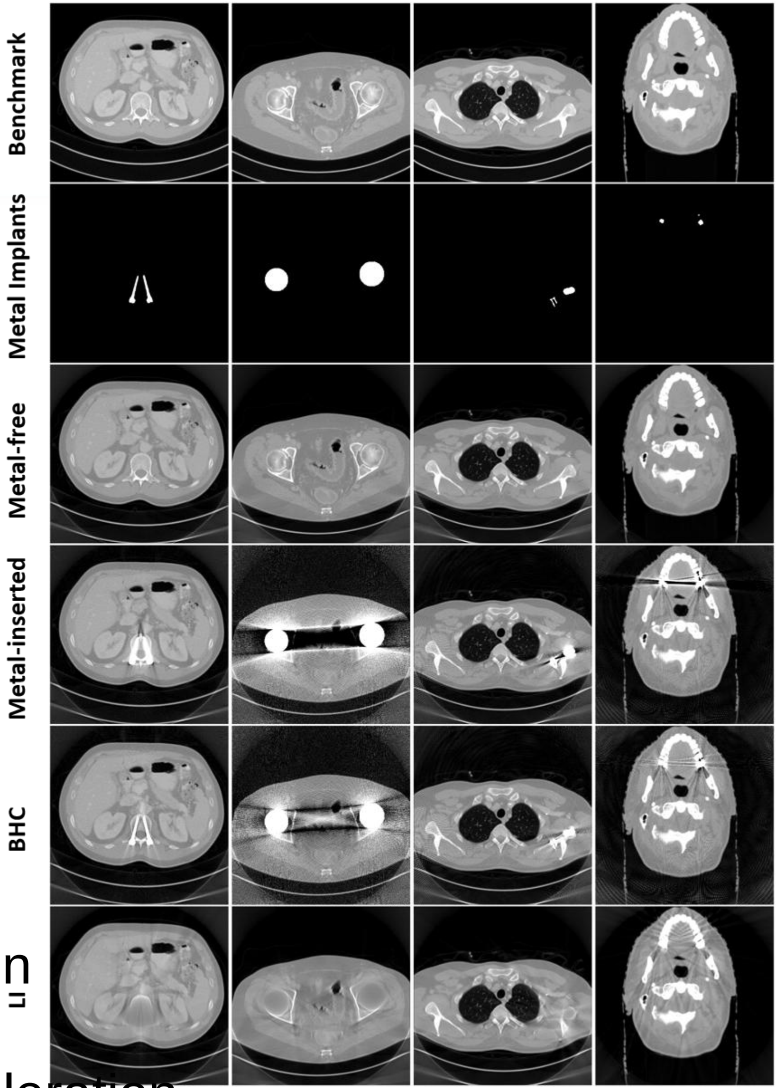


Comparison of sinogram completion. An ROI is enlarged and displayed with a narrower window.

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



Convolutional Neural Network (CNN) Training

- 10,000 training data
- Data: 80% for training, the rest for validation
- Matlab with the MatConvNet Toolbox
- GeForce GTX 970 GPU was used for acceleration

Experiments

Numerical Simulation

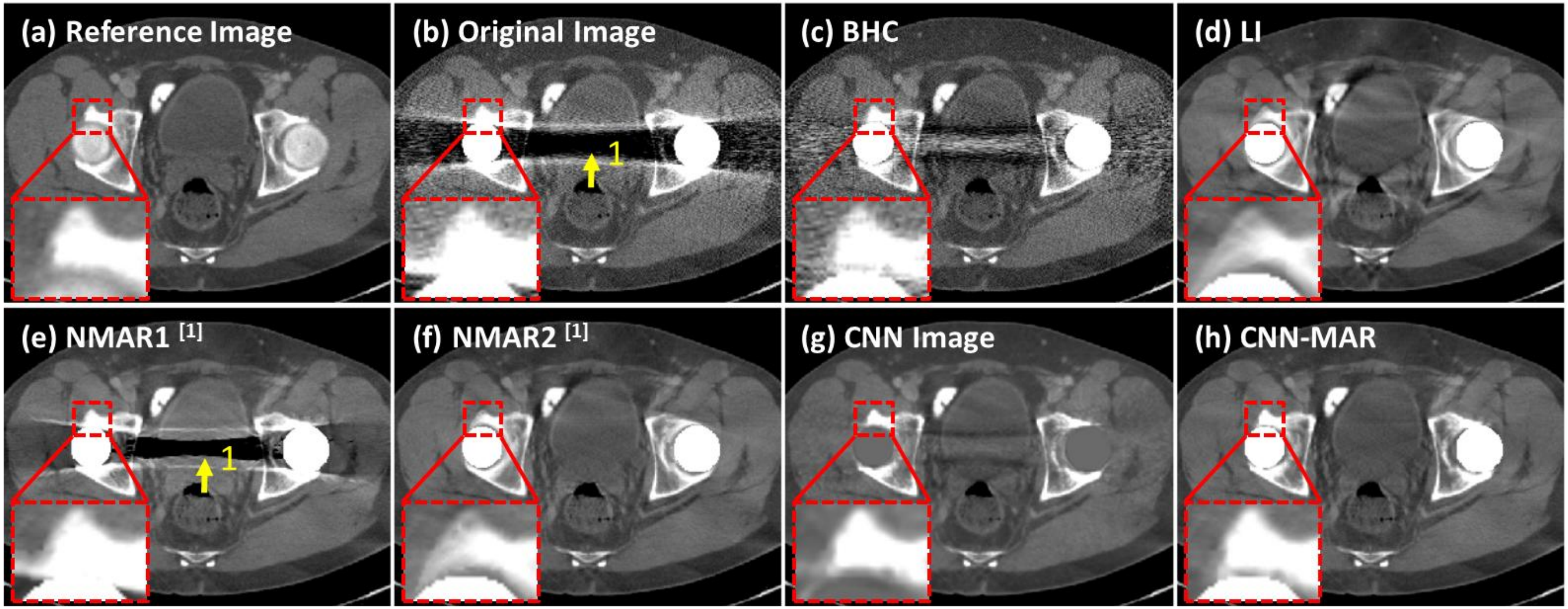
- Case 1: hip prostheses
- Case 2: fixation screws
- Case 3: dental fillings
- Same simulation parameters to that of cases in the database

Real Data

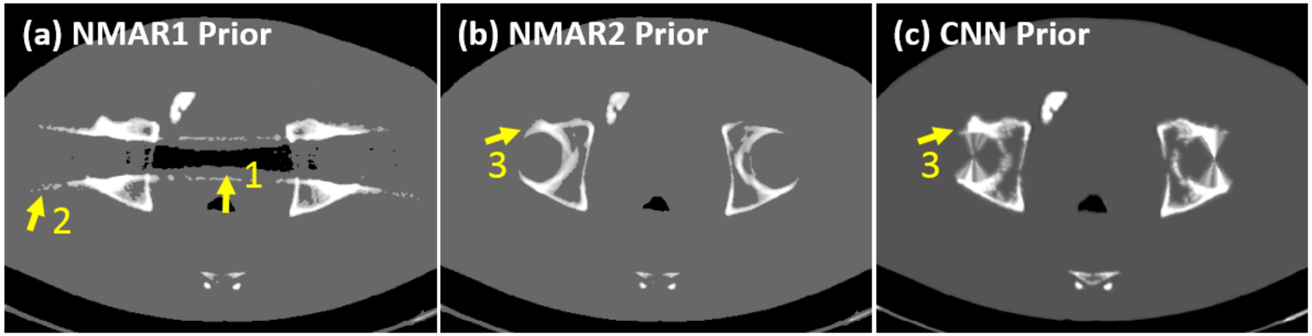
- A 59-year old female patient with a surgical clip
- Siemens SOMATOM Sensation 16 CT scanner
- 120 kVp and 496 mAs
- 1160 projection views per rotation
- 672 detector bins in a raw

Simulation

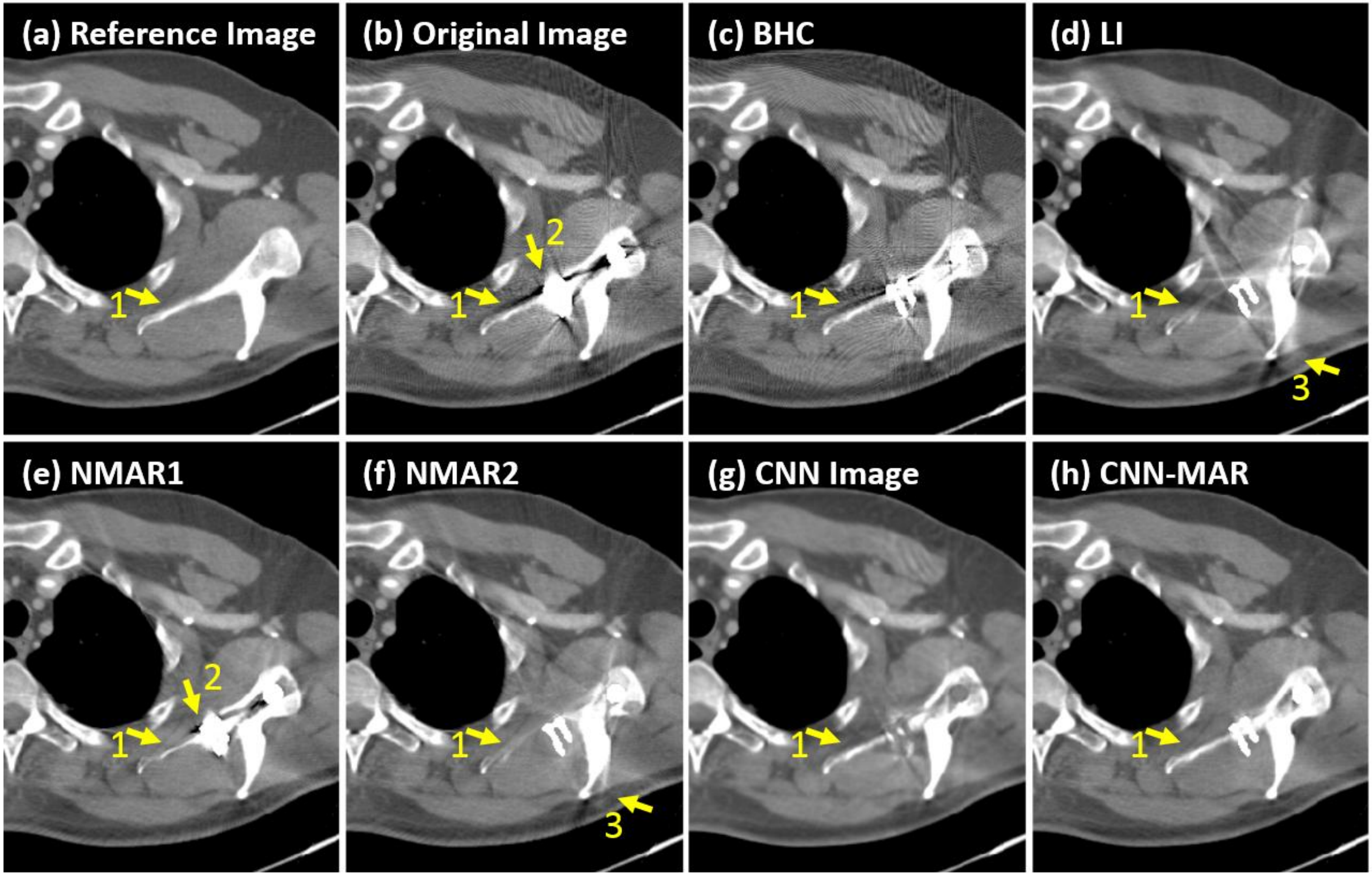
Case 1: bilateral hip prostheses.



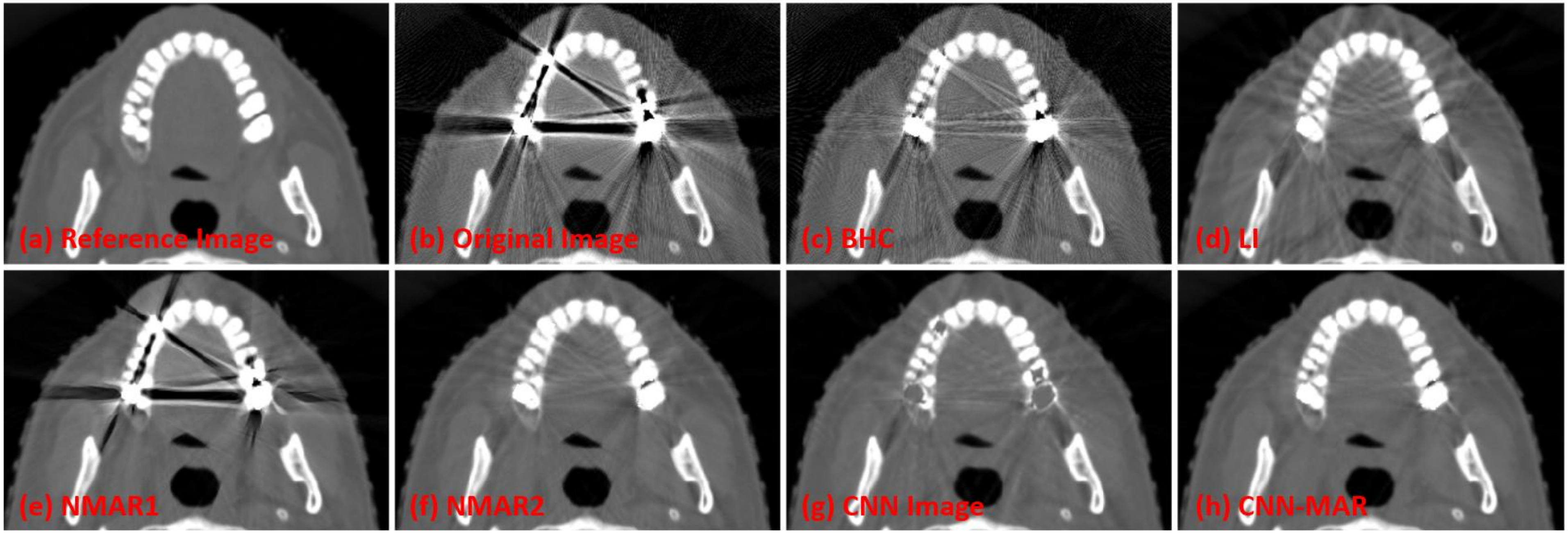
Prior images:



[1] E. Meyer, R. Raupach, M. Lell, B. Schmidt, and M. Kachelriess, "Normalized metal artifact reduction (NMAR) in computed tomography," *Medical Physics*, vol. 37, pp. 5482-5493, 2010.



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



Case 3: four dental fillings.

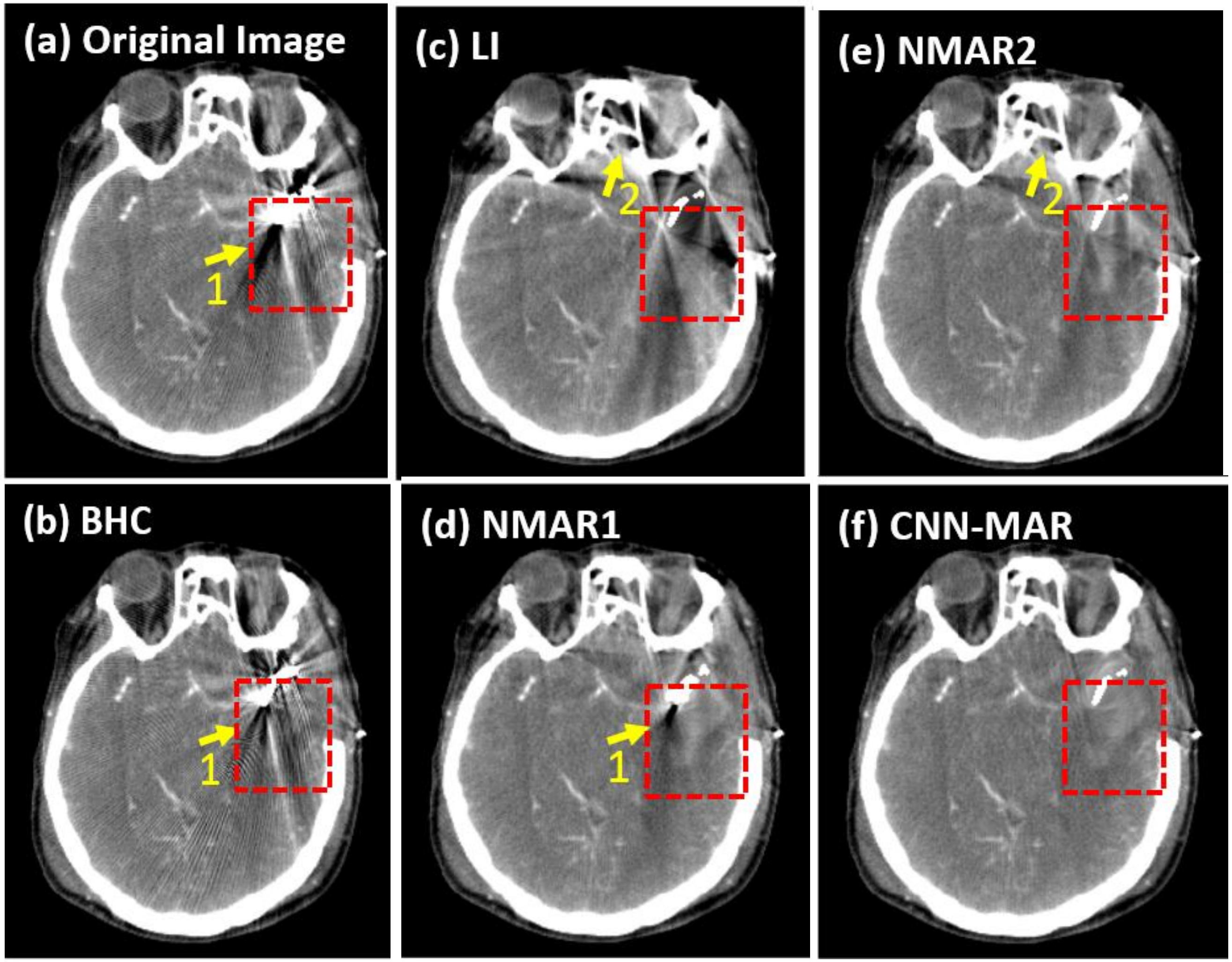
Table I. RMSE of each image in the numerical simulation study. (Unit: HU).

	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

Clinical Data

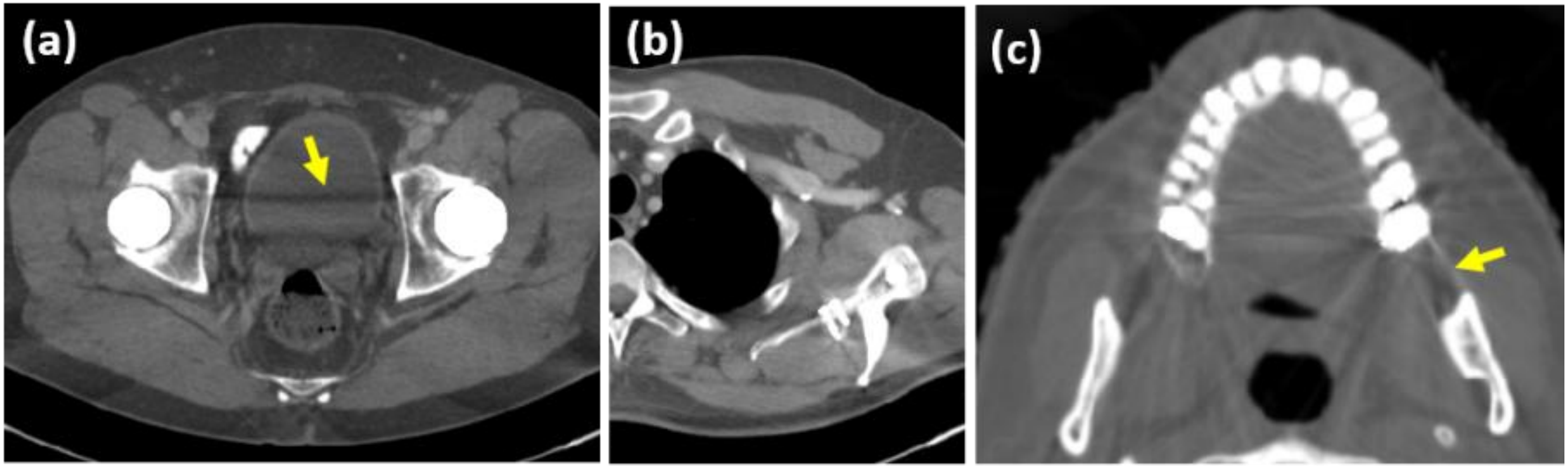


A 59 year-old female with diffused subarachnoid hemorrhage (highlighted by the red square). CT angiography demonstrated a left middle cerebral artery aneurysm, which was clipped. The display window is [-100 200] HU.

Discussion

Effectiveness of the Tissue Processing

- Reduce artifacts remained in the CNN image

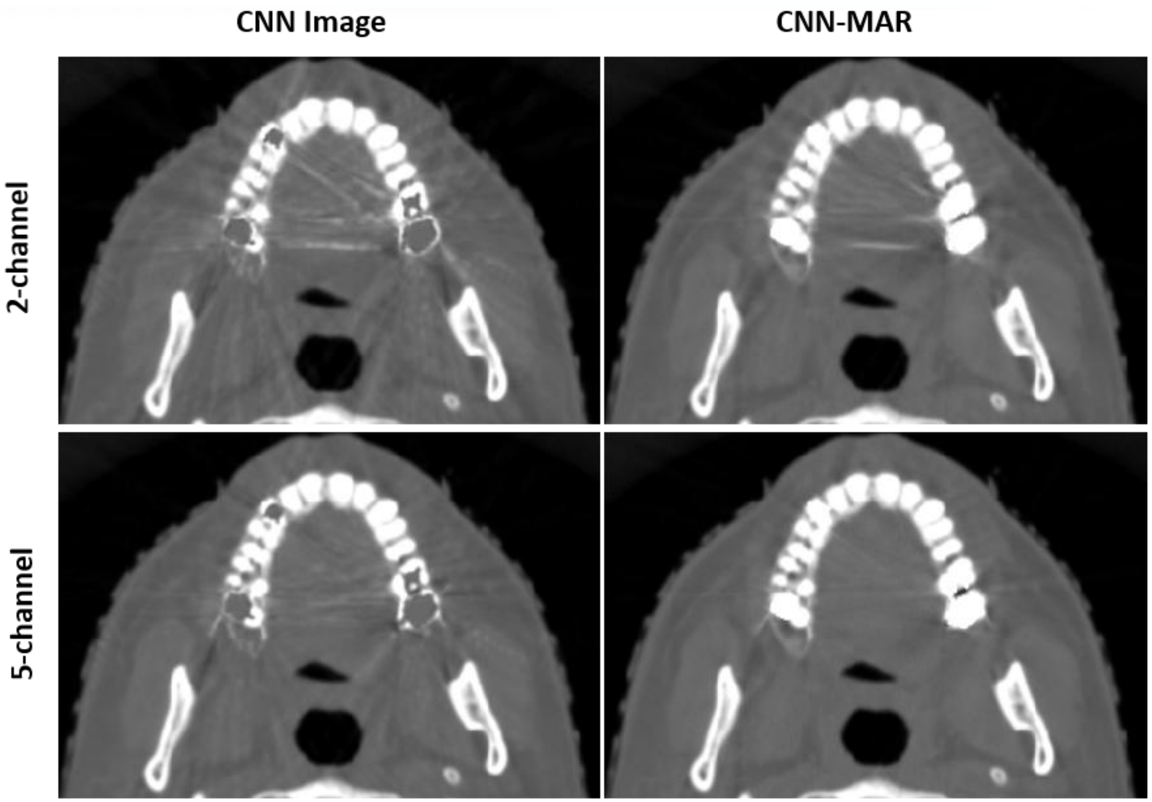


Results obtained by directly adopting a CNN image as the prior image without the tissue processing step. (a)-(c) corresponds to the cases 1-3, respectively.

Discussion

Selection of Input Images (MAR Methods)

- 2-channel: Original + LI
- 5-channel: Original + BHC + LI + NMAR1 + NMAR2
- ***Key:*** If new information is introduced?

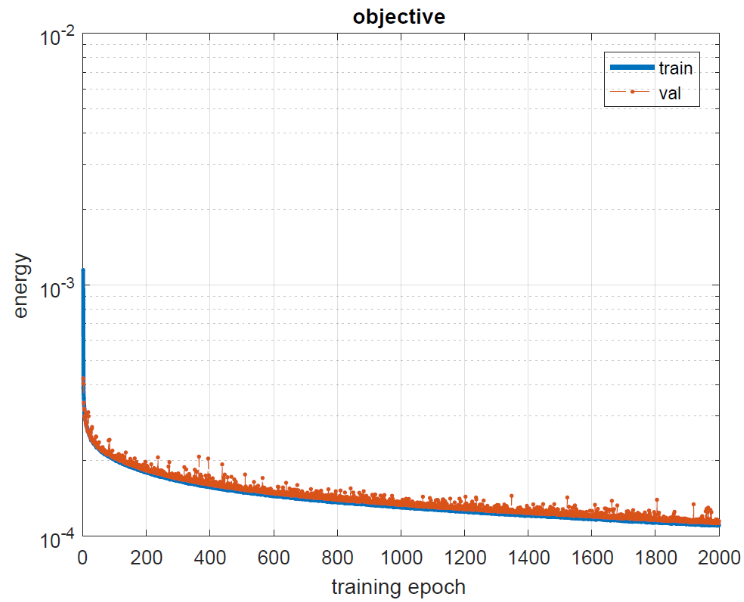


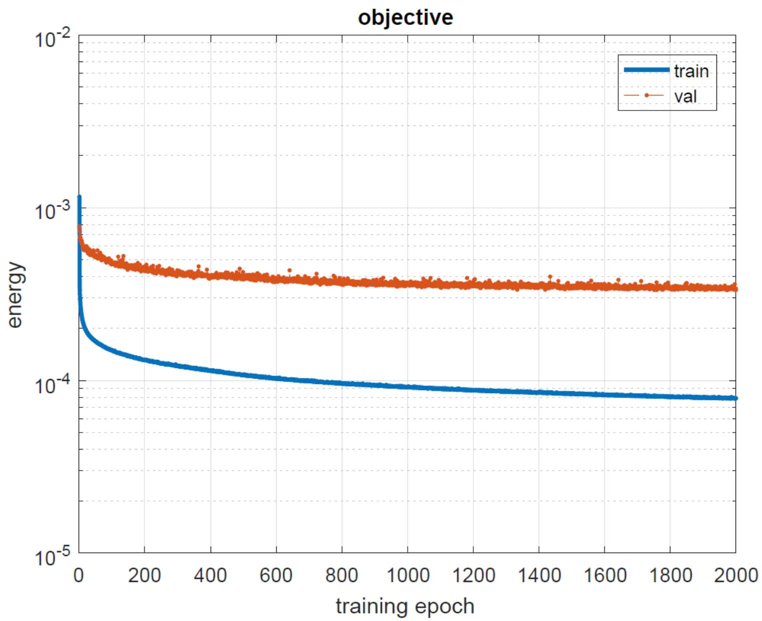
Case 3: CNN and CNN-MAR results based on two- and five-channel input images.

Discussion

Training Data and Epochs

- A good CNN image can be obtained after 200 epochs
- CNN-MAR can be improved by introducing various cases as the training data





The convergence curves of CNN training in terms of energy of loss function versus training epochs. Left: Training data and validation data are selected from the same dataset. Right: Training data and validation data are from different cases in the dataset.

Future Work

1. Fully Convolutional Network (FCN)[1] based MAR

- Advantage: Semantic segmentation
- Metal segmentation: The trained FCN could segment out metal implants more precisely

2. ResNet[2] based MAR

- Advantage: A more powerful CNN model
- Simplify the proposed MAR framework: Due to the superior capacity of ResNet, the tissue processing can be carried out with the network.

[1] Long, Jonathan, Evan Shelhamer, and Trevor Darrell. "Fully convolutional networks for semantic segmentation." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2015.
[2] He, Kaiming, et al. "Deep residual learning for image recognition." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016.

Summary

CNN-MAR

Capture information from various images

Depend on the training data

More MAR results can be incorporated

Artifact Reduction

Structure Preservati on

Open Framework

Thank You!