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)

- Dual energy
- Physics model
  - Denoising and BHC
  - Polychromatic iterative reconstruction
- MAR using incomplete data
  - Iterative Reconstruction
  - Projection Completion
  - Interpolation
  - Forward projection of a prior image
Metal Artifact Reduction (MAR)

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

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Workflow of The Proposed CNN-MAR

Original Sinogram → FBP → Original Image → BHC Image → LI Image

Metal Segmentation → Metal Only Image → Forward Projection → Metal Trace

CNN Image → Tissue Processing → CNN Prior

Metal Trace Replacement → Corrected Sinogram

Insert Back → CNN-MAR Image

Forward Projection → FBP
**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.

Less artifacts!
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:

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).

<table>
<thead>
<tr>
<th></th>
<th>Original</th>
<th>BHC</th>
<th>LI</th>
<th>NMAR1</th>
<th>NMAR2</th>
<th>CNN</th>
<th>CNN-MAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>155.0</td>
<td>86.3</td>
<td>46.2</td>
<td>121.2</td>
<td>35.4</td>
<td>33.1</td>
<td>29.1</td>
</tr>
<tr>
<td>Case 2</td>
<td>71.5</td>
<td>44.4</td>
<td>54.5</td>
<td>50.4</td>
<td>41.4</td>
<td>31.5</td>
<td>22.8</td>
</tr>
<tr>
<td>Case 3</td>
<td>320.3</td>
<td>183.5</td>
<td>107.3</td>
<td>234.9</td>
<td>82.3</td>
<td>83.4</td>
<td>58.4</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th></th>
<th>Original</th>
<th>BHC</th>
<th>LI</th>
<th>NMAR1</th>
<th>NMAR2</th>
<th>CNN</th>
<th>CNN-MAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>0.565</td>
<td>0.576</td>
<td>0.930</td>
<td>0.887</td>
<td>0.935</td>
<td>0.940</td>
<td>0.943</td>
</tr>
<tr>
<td>Case 2</td>
<td>0.883</td>
<td>0.854</td>
<td>0.931</td>
<td>0.955</td>
<td>0.950</td>
<td>0.965</td>
<td>0.977</td>
</tr>
<tr>
<td>Case 3</td>
<td>0.522</td>
<td>0.536</td>
<td>0.886</td>
<td>0.833</td>
<td>0.942</td>
<td>0.932</td>
<td>0.967</td>
</tr>
</tbody>
</table>
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

   - 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.

Summary

CNN-MAR

- Capture information from various images
- Depend on the training data
- More MAR results can be incorporated

Thank You!