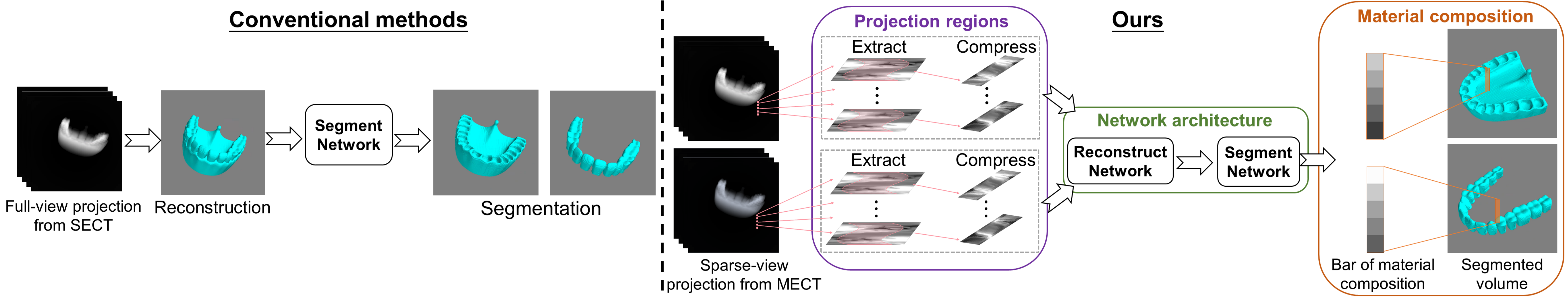# End-to-End Deep Learning for Reconstructing Segmented 3D CT Image from Multi-Energy X-ray Projections

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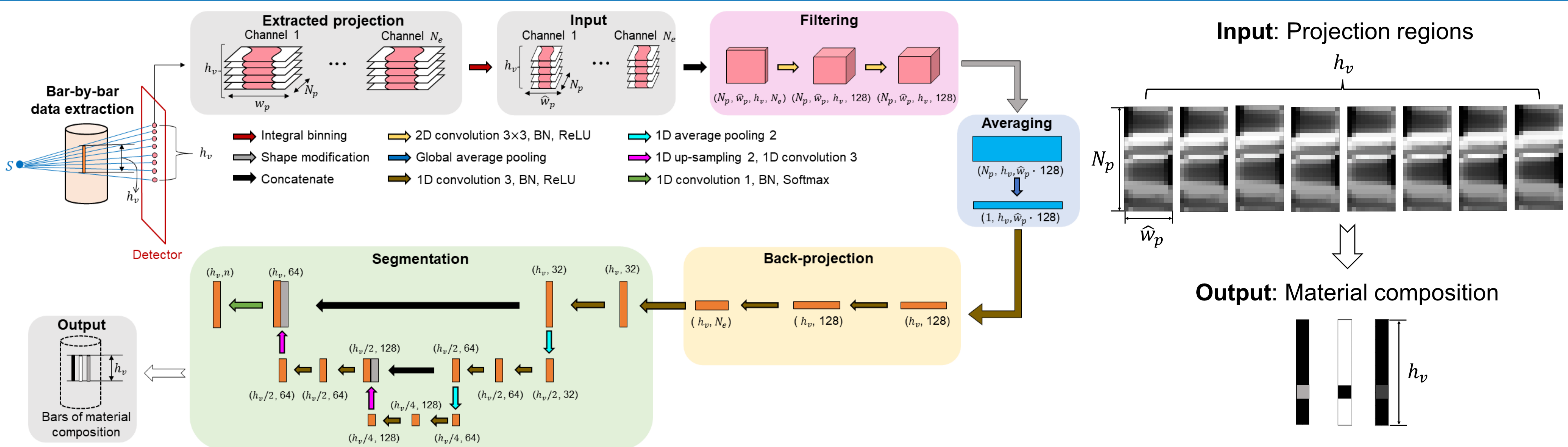
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Introduction

Conventional methods: Full-view projection from SECT → Reconstruction → Segment Network → Segmentation

Ours: Sparse-view projection from MECT → Projection regions (Extract, Compress) → Network architecture (Reconstruct Network → Segment Network) → Material composition (Bar of material composition, Segmented volume)

◆ Conventional DL-based segmentation needs "reconstructed" CT ⟹ Propose end-to-end segmentation to eliminate artifacts from reconstruction algorithms.

◆ High memory demand for inputting 3D CT data ⟹ Implement discrete learning to segment large-scale data.

◆ Limitations in material discrimination with single-energy CT (SECT) ⟹ Integration of multi-energy CT (MECT) to enhance segmentation quality.

Network architecture

Bar-by-bar data extraction

Extracted projection: Channel 1 ... Channel N_e, h_v, w_p, N_p

Input: Channel 1 ... Channel N_e, h_v, $\hat{w}_p$, N_p

Filtering: $(N_p, \hat{w}_p, h_v, N_e)$, $(N_p, \hat{w}_p, h_v, 128)$, $(N_p, \hat{w}_p, h_v, 128)$

Averaging: $(N_p, h_v, \hat{w}_p \cdot 128)$, $(1, h_v, \hat{w}_p \cdot 128)$

Back-projection: (h_p, N_e), $(h_p, 128)$, $(h_p, 128)$

Segmentation: (h_v, n), $(h_v, 64)$, $(h_v, 32)$, $(h_v, 32)$, $(h_v/2, 128)$, $(h_v/2, 64)$, $(h_v/2, 64)$, $(h_v/2, 32)$, $(h_v/2, 64)$, $(h_v/2, 32)$, $(h_v/4, 128)$, $(h_v/4, 128)$, $(h_v/4, 64)$

Output: Bars of material composition, h_v

Legend:
- Integral binning
- Shape modification
- Concatenate
- 2D convolution 3×3, BN, ReLU
- Global average pooling
- 1D convolution 3, BN, ReLU
- 1D average pooling 2
- 1D up-sampling 2, 1D convolution 3
- 1D convolution 1, BN, Softmax

Input: Projection regions — h_v, N_p, $\hat{w}_p$
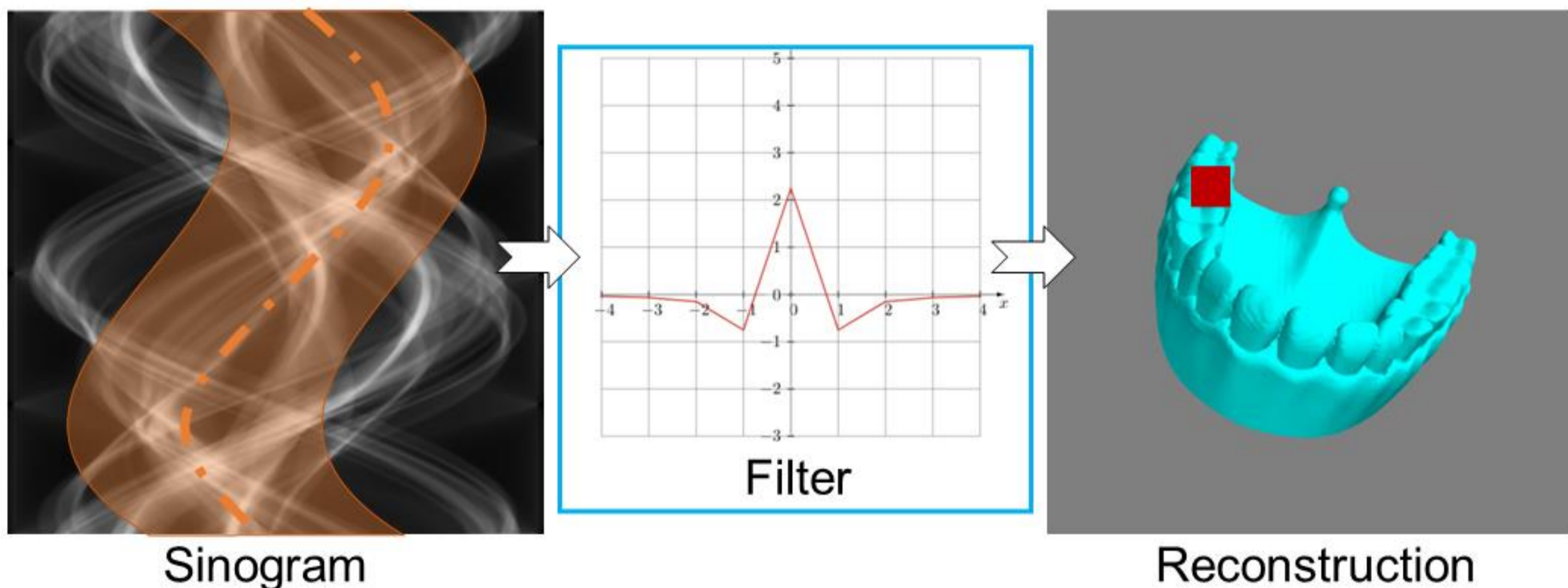
Output: Material composition — h_v
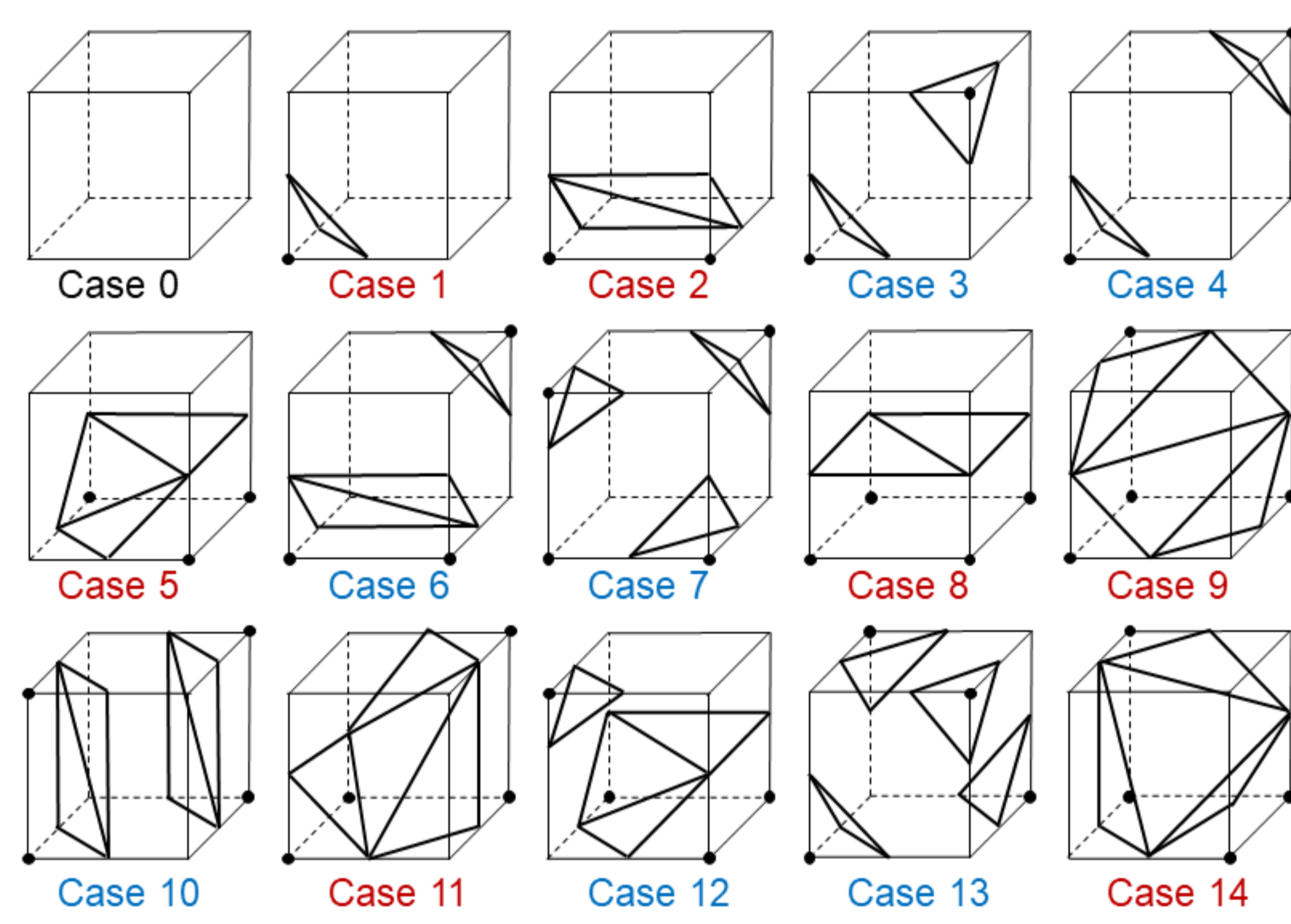
Projection extraction based on filtered back-projection

$$f(x,y,z) = \frac{1}{2}\int_0^{2\pi} U^{-2}(x,y,\theta)\,d\theta \int_{-\infty}^{+\infty} p(X',Z,\theta)\,l(X'-X)\cos\phi(X',Z)\,dX'$$

Extension of sinusoid → Sinogram

Filter

One reconstruction voxel → Reconstruction

Material composition extraction for each voxel

Case 0, Case 1, Case 2, Case 3, Case 4, Case 5, Case 6, Case 7, Case 8, Case 9, Case 10, Case 11, Case 12, Case 13, Case 14
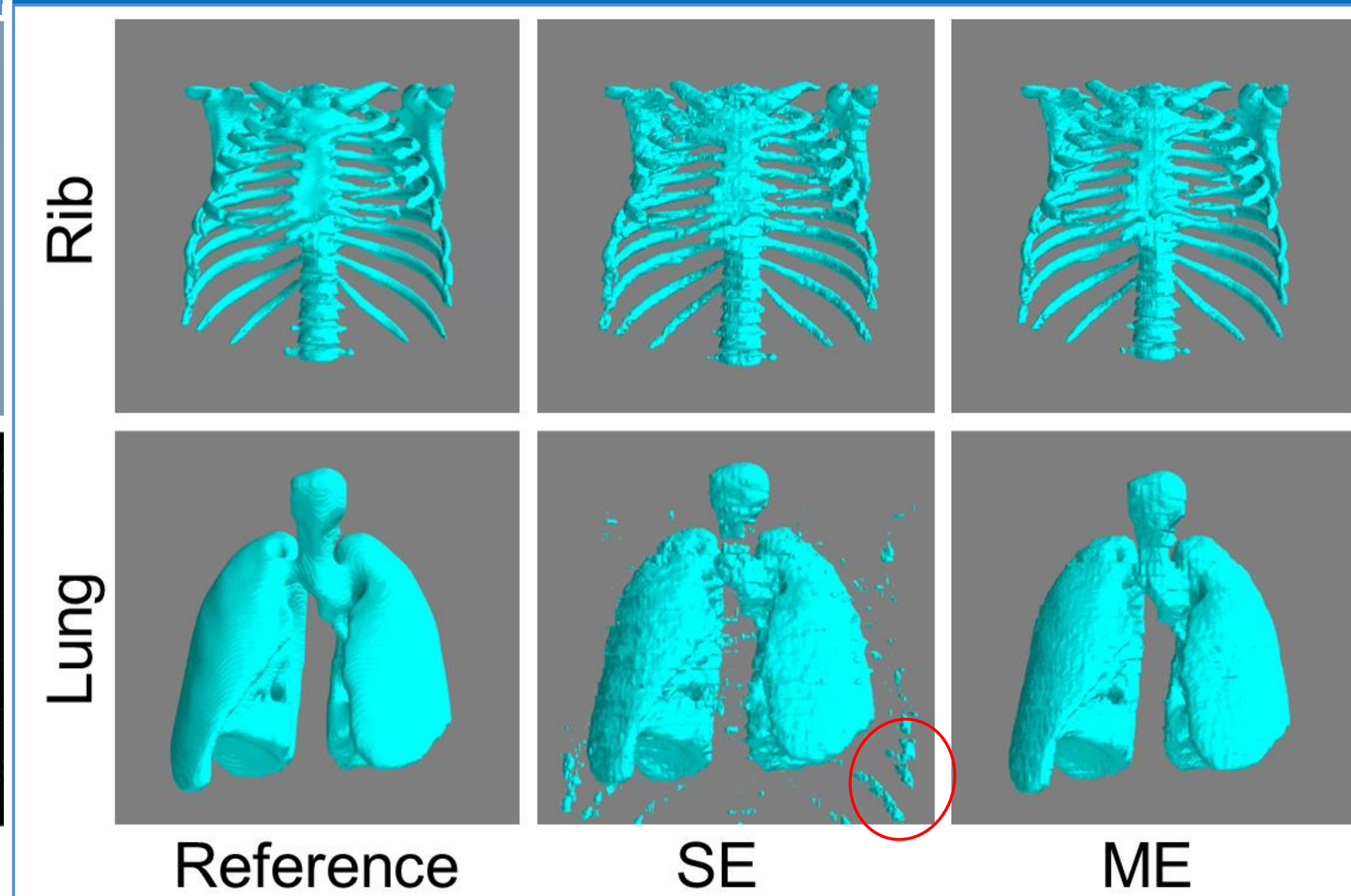
1. Reconstruct the separate scanning of each part and obtain the iso-surface.
2. Classify the voxels containing iso-surfaces into two types: connected and separated.
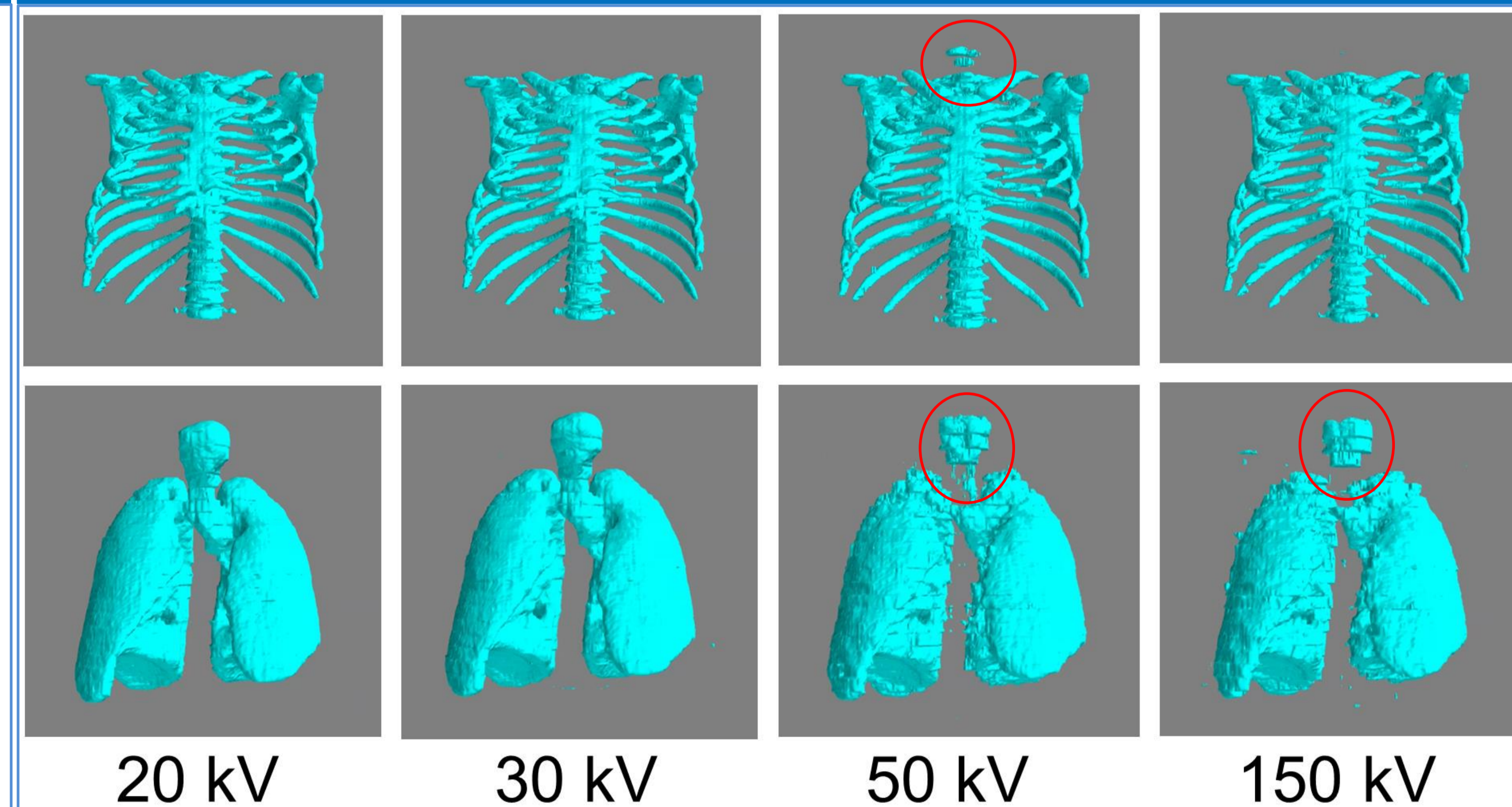3. For connected, the ration of material composition is $V(P_k)/s^3$; For separated, $1 - V(P_k)/s^3$

Experiment samples

3D model / Reconstruction — Chest-A, Chest-B
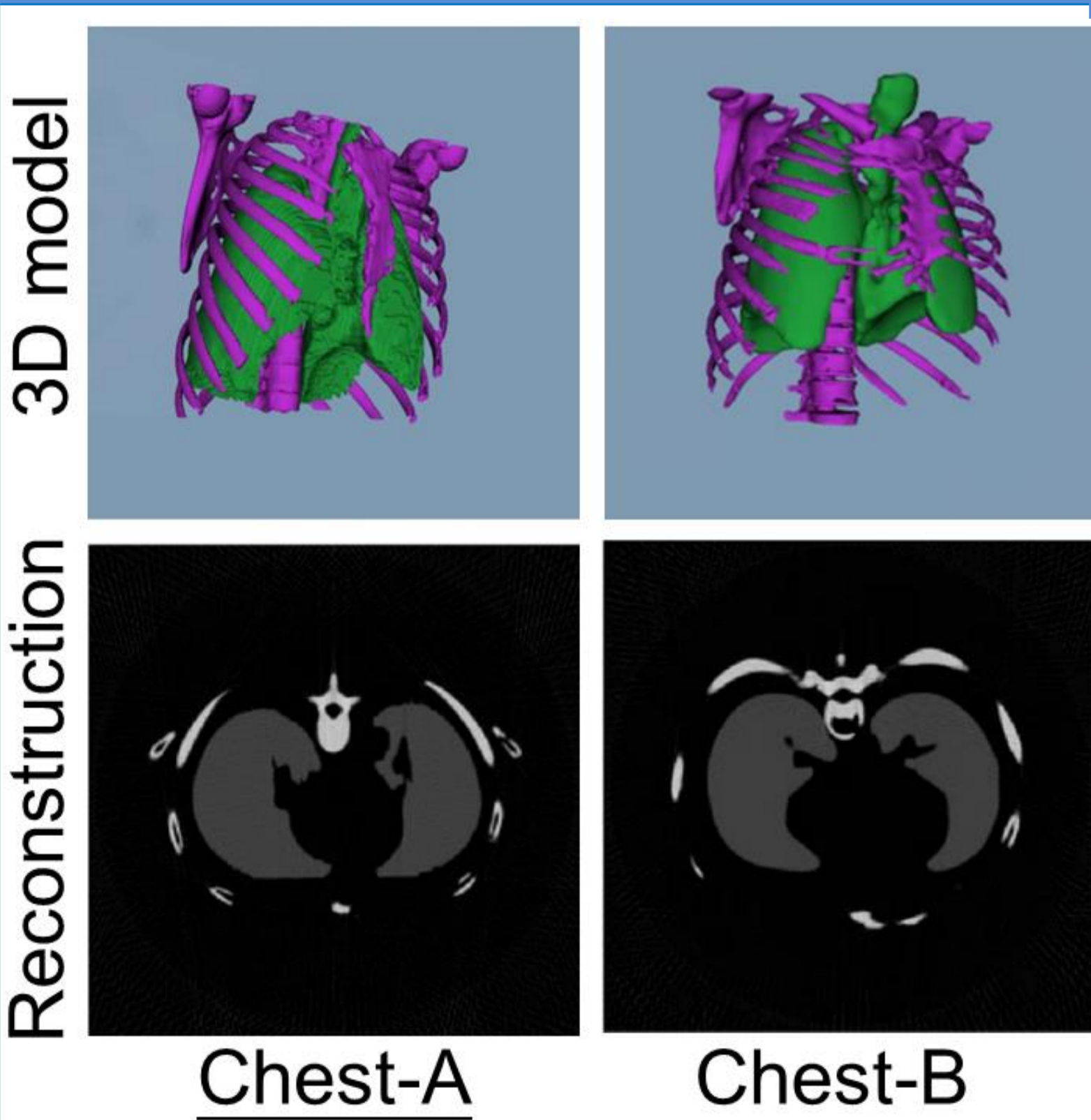
Multi-energy vs Single-energy

Rib / Lung — Reference, SE, ME

Different energy resolutions

Rib / Lung — 20 kV, 30 kV, 50 kV, 150 kV

Dice coefficients and processing time

	SE (80-100kV)	20 kV 8 bins	30 kV 5 bins	50 kV 3 bins	150 kV 1 bin
DICE	0.960	0.986	0.985	0.980	0.978
Time	20 min	33 min	30 min	26 min	20 min

Future plan and related work

◆ Enhance a filtering module to focus more on the varying contributions of energy bins.

[1] Siqi Wang, Tatsuya Yatagawa, Yutaka Ohtake, Hiromasa Suzuki. "Sparse-View Cone-Beam CT Reconstruction by Bar-by-Bar Neural FDK Algorithm". Nondestructive Testing and Evaluation, 2023.