

## Improving segmentation of FIB tomography data

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### Background incl. aims

Accurate reconstruction of nanostructures using focused ion beam (FIB) tomography data is challenging due to slicing and imaging artefacts, as well as intensity ambiguities in the scanning electron microscope backscattered electron (BSE) images. We propose a multimodal machine learning approach that combines intensity information obtained at multiple electron beam accelerating voltages (multiV) to improve the three-dimensional (3D) reconstruction of hierarchical nanoporous gold (HNPG) structures. The proposed method significantly improves segmentation accuracy and leads to more precise 3D reconstructions for real FIB tomography data.

### Methods

MultiV FIB tomography of epoxy infiltrated HNPG with ligament sizes of 15 nm and 110 nm was performed using a Dual Beam FEI Helios NanoLab G3 system and its ASV4 control software for automated tomography. During multiV tomography, each slice was imaged using a BSE detector three times with accelerating voltages of 1, 2, and 4 kV and a beam current of 50 pA. To compensate for drift during the process, 2 fiducial markers were prepared and positioned on the cross-section and on top of it. A ruler system was implemented also on top of the cross-section to monitor and measure the thickness of each slice. We developed 3 multimodal architectures for 3D nanostructure reconstruction with machine learning, employing different data fusion techniques: early fusion, intermediate fusion and late fusion.

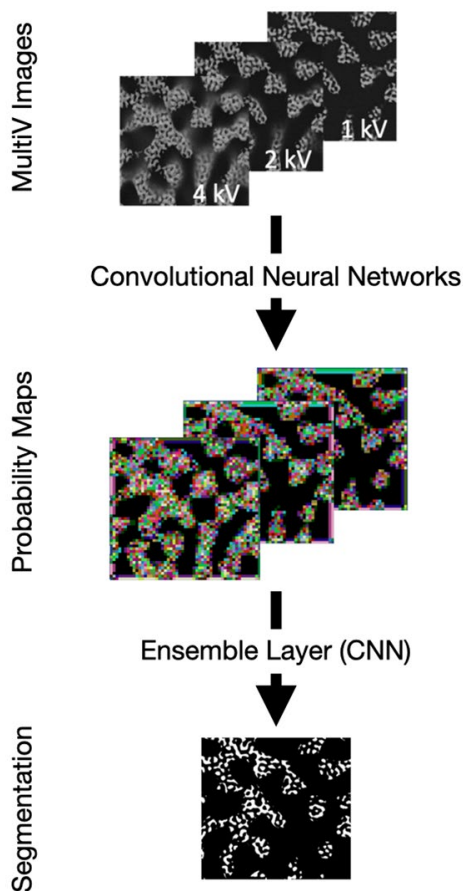
### Results

Our results indicate that the late fusion architecture excelled among the three options. Remarkably, the intermediate fusion architecture exhibited significantly poorer metrics than the late fusion architecture. This drop in performance can be attributed to the large size of the ML model, which posed challenges for optimization given a limited amount of training data. However, the effectivity of training data may be improved using domain adaptation. In a comparative study, confronting our ML-multiV method with a cluster-based k-means clustering algorithm and also ML models trained using individual single kV datasets, the multiV model outperformed all other segmentation techniques.

### Conclusion

FIB-SEM tomography data are affected by artifacts and ambiguities in image intensities. These effects make it difficult to use cluster-based segmentation methods. More advanced ML-based methods can efficiently suppress the effects, even when trained only on a single set of synthetic FIB tomography images. The multimodal ML method with a late fusion architecture using multiV imaging data will further improve segmentation accuracy.

**Graphic:**



**Keywords:**

FIB tomography, multimodal ML, segmentation

**Reference:**

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