Supplementary Materials for:

Convolutional Neural Network for Segmenting Micro-X-Ray Computed Tomography Images of Wood Cellular Structures

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Traditional Histogram-based Segmentation Methods

For traditional histogram-based image segmentation methods to be successful, the histogram of a grayscale image containing different object classes would need to be multimodal with each class having a specific modal value. This multimodal histogram is exploited by traditional histogram-based image segmentation methods to gather the different objects into classes. As observed in the histograms in Figures 4c and d and the top of Figure S1, the histograms of the reconstructed grayscale µXCT images of wood in this work were not multimodal. Nevertheless, because of the simplicity of the traditional histogram-based thresholding, different thresholding methods were tested using the auto threshold plugin of ImageJ (Schneider et al. 2012) as shown in Figure S1. Traditional threshold methods did not perform well. In general, the histogram-based thresholding methods were able to segment the edges of the sample. However, often the interior pixels of the sample were misclassified. It can be observed that qualitatively the U-Net CNN segmentation developed in this work is the closest to the ground-truth image.

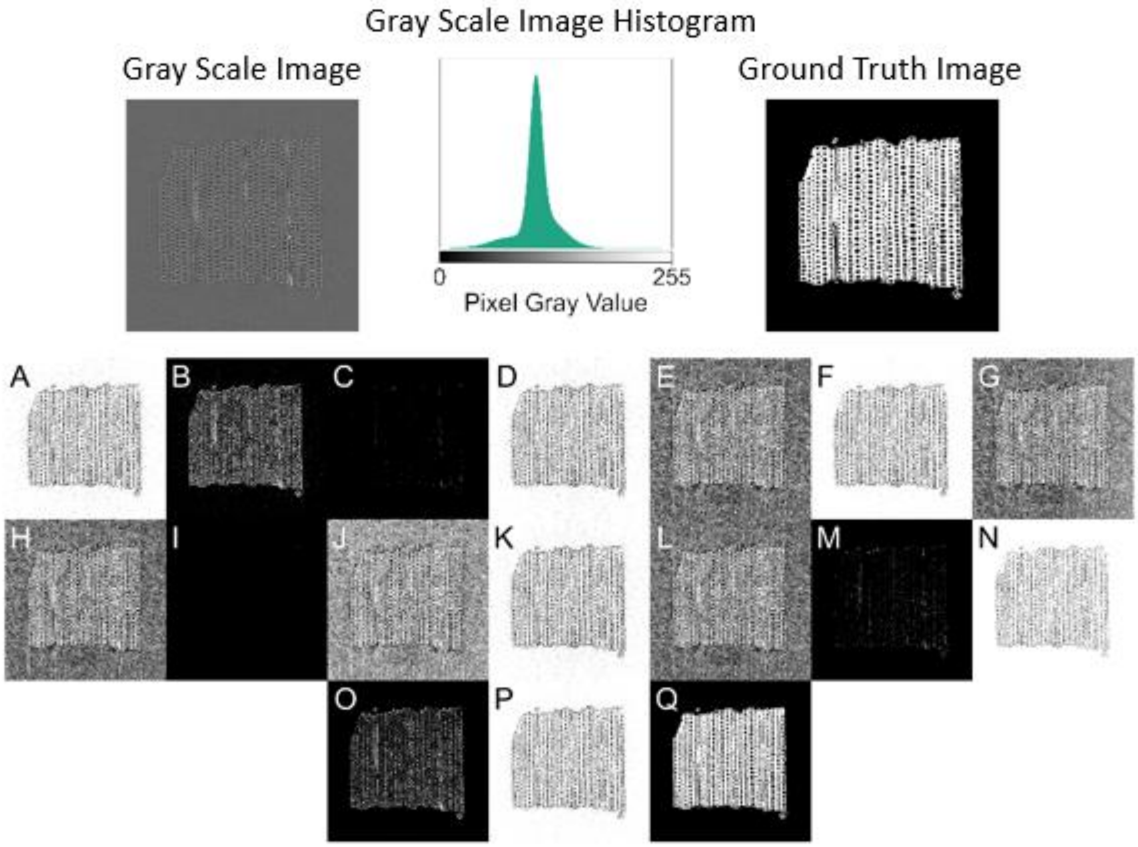
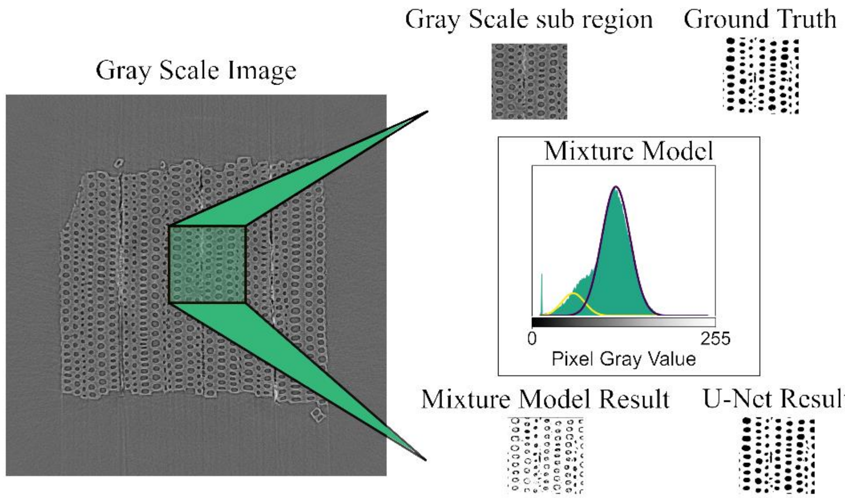


Figure S1: Binary image comparison between different histogram-based thresholding segmentation methods and the modified U-net CNN developed in this work. At the top, the original gray-scale image with the histogram and the ground-truth image are shown. At the bottom the different segmentation methods are shown: A) Default, B) Huang (Huang and Wang 1995), C) Intermodes (Prewitt and Mendelsohn 1966), D) Isodata (Ridler and Calvard 1978), E) Li Minimum Cross Entropy (Li and Lee 1993), F) Maximum Entropy (Kapur et al. 1985), G) Mean of Grey Levels (Glasbey 1993), H) Minimum Error (Kittler and Illingworth 1986), I) Minimum of Grey Values (Prewitt and Mendelsohn 1966), J) Moments (Tsai 1985), K) Otsu (Otsu 1979), L) Percentile (Doyle 1962), M) Renyi Entropy (Kapur et al. 1985), N) Shanbhag (Shanbhag 1994), O) Triangle (Zack et al. 1977), P) Yen (Yen et al. 1995), Q) U-Net (Ronneberger et al. 2015).

A more complex segmentation method that has been used to segment µXCT images of wood is the Gaussian mixture model (Jakes et al. 2019; McKinley et al. 2016). In the Gaussian mixture model the histogram is fit to a series of Gaussian distributions. The number of Gaussian distributions corresponds to the expected number of object classes in the image. For the wood µXCT images in this study, two object classes corresponding to cell wall and air would be expected. Unfortunately, the characteristic histograms of the full gray-scale images could not be properly fitted with two Gaussians. Nevertheless, we partitioned the images into a sub region that was located inside of the wood (**Figure S2**). In the sub region, the peaks of each phase were better defined in the histogram with a main peak and more obvious shoulder. The fitted Gaussian peaks are shown in Figure S2. However, the overlap between the valleys reduced the segmentation accuracy. It can be seen in the mixture model binary image that pixels corresponding to air were assigned to the cell wall.



<u>Figure S2:</u> Gaussian Mixture Model segmentation method of image sub region compared to U-Net segmentation.

We also used the IoU metric (Equation 1) to quantitatively compare the results from the different histogram-based segmentation methods with the U-Net CNN segmentation. As shown in **Figure S3**, most histogram-based segmentation methods scored an IoU between 30% and 50% and U-Net CNN scored an IoU of 96%. The IoU was also calculated for the sub region segmentations. The Gaussian mixture model scored an IoU of 84% in the sub region while U-Net CNN scored 98%. These results clearly demonstrate the need for the U-net CNN segmentation to reliably segment the fast propagation-based phase-contrast µXCT images of cellular materials like those of wood obtained in this study.

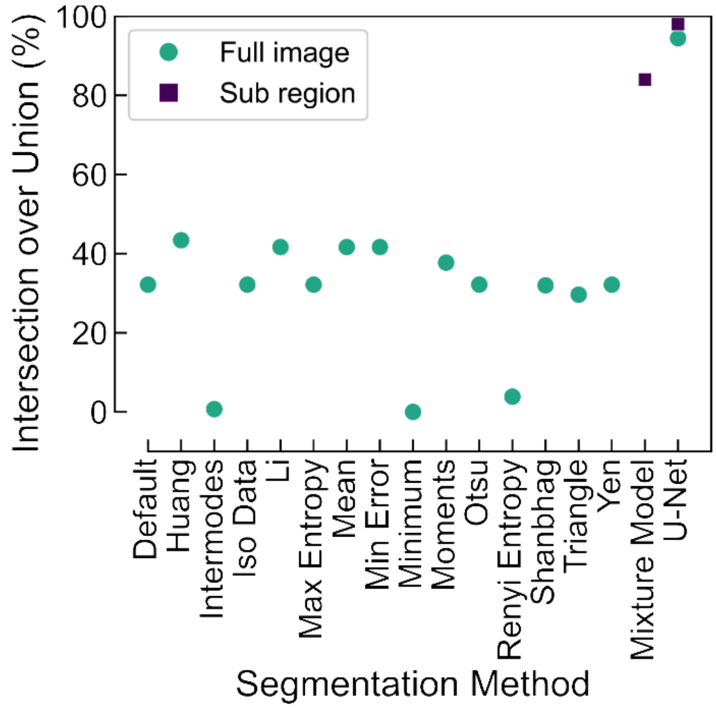


Figure S3: Scores of Intersection over Union (IoU) of the different segmentation methods.

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