

Quantifying Feature Uncertainty in Sub-sampled Low-dose (S)TEM Images

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Scanning transmission electron microscopes (STEM) provide high resolution images at an atomic scale. Unfortunately, the level of electron dose required to achieve these high resolution images results in a potentially large amount of specimen damage. A promising approach to mitigate specimen damage is to subsample the specimen [1, 2, 3]. With random sampling, the microscope creates high resolution images of segments of the specimen while reducing overall damage. However, subsampling produces images that have several missing values and can be hard to interpret and analyze in their raw state.

In order to make the subsampled images more interpretable, several methods have been proposed to recreate the full images from the subsampled images (inpainting). Most notable among them is compressive sensing, which has been shown to be an extremely accurate in a variety of domains [2]. Once the image is reconstructed, any appropriate image processing technique could be used to quantify features of the reconstructed image to estimate the same features in the full image. Alternatively, one could quantify the features in the subsampled images directly and scale those estimates to the full image appropriately (extrapolation).

To illustrate the extrapolation approach, consider the lithium battery experiment described in [4]. A principal goal of that experiment was to quantify the amount of lithium dendrite that grew at the anode/electrolyte interface. In Figure 1, the fully sampled image is presented in the cell labelled "Data" along with the results of an example quantification method based on five different degrees of subsampling. The extrapolation approach to estimating the total amount of growth in the subsampled frames would be to estimate the growth based on the sampled frames and multiply that estimate by the inverse of the sampling proportion.

Results of the extrapolation approach for the Mehdi et al. data sampled at 5% and 1% are given in Figure 2. Because there is no growth early in the video, we approximate the bias of this method to be about $5/\mu\text{m}^3$ for both sampling rates. Removing this bias would make the results in Figure 2 roughly match those published in Figure 5(b) of [4]. As expected, the width of the uncertainty bounds (indicated by dashed lines in Figure 2) is inversely related to the subsampling rate, i.e., the uncertainty bounds get wider as the number of pixels sampled goes down.

In this presentation we further explore the bias and uncertainty introduced by the in-painting and extrapolation approaches to feature quantification of sub-sampled STEM images. Our goal is to provide STEM operators with the tools necessary to make informed decisions about how much dose to use when conducting their experiments as it relates to feature uncertainty. Several existing, high impact STEM experiments are used to illustrate our results [5].

References

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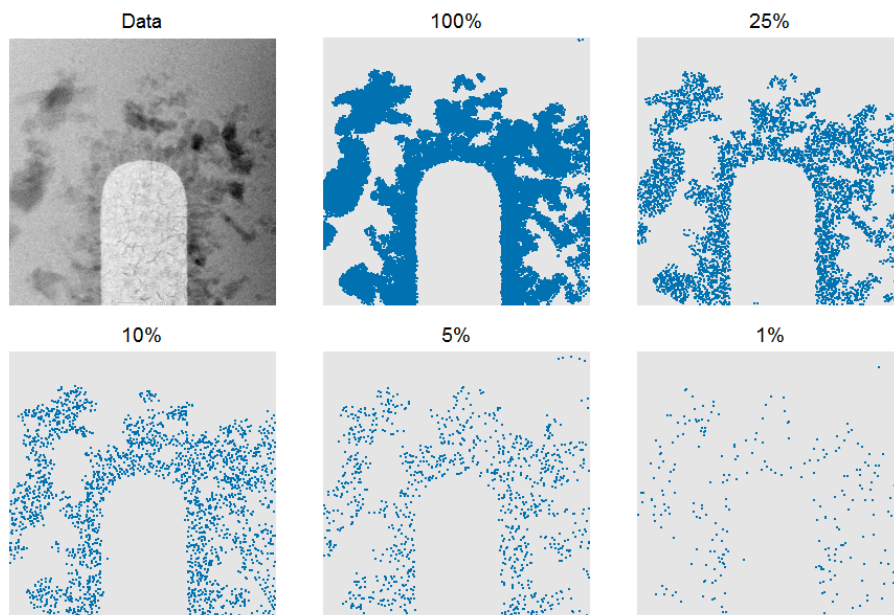


Figure 1: One frame from [4] (labelled "Data") along with the results of a feature quantification method for various subsampling levels. The blue pixels were classified as lithium dendrite growth.

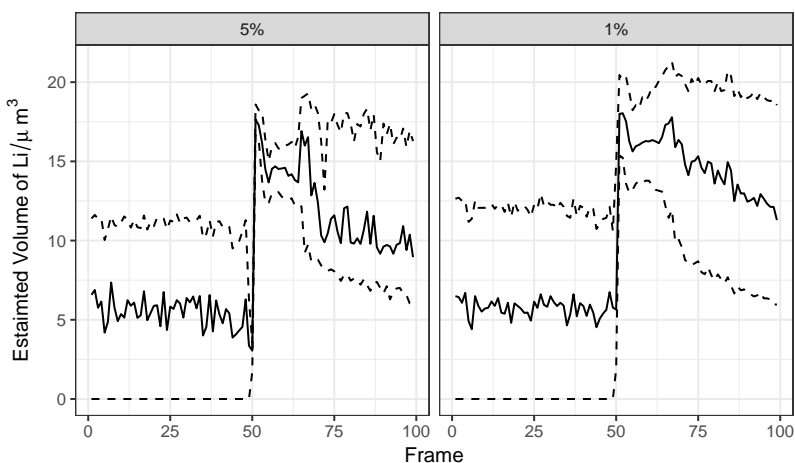


Figure 2: Estimated volume (solid line) with uncertainty bounds (dashed line) of Li dendrites growth under subsampling.