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Self-Organizing Neural Networks: Parallels Between "Big Imaging" and Sparse Imaging in Electron Microscopy

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We are witnessing interesting parallels in the microscopy community between extremely large datasets and sparse, under-sampled versions of traditional images. Ironically, methods to reduce the negative impact of electron/radiation dose by sampling fewer pixels tend to produce excessively large datasets per image [1]. Patch-based image reconstruction methods, such as hierarchical Bayesian models and non-local means methods, achieve state-of-the-art results by producing an over complete feature space through expanding the image into a large number of overlapping patches. Many model parameters are learned iteratively from these patches, producing a large and higher dimensional data space in which information about features and image information is captured. New ideas and techniques to exploit this large feature space are urgently required to fully realize the potential benefits from real-space under sampling.

On the other end of the spectrum, extremely high brightness electron sources coupled to the obvious benefits of aberration correctors are producing extraordinarily large datasets with correlated temporal or chemical information [2]. Energy loss spectroscopy (EELS) and energy dispersive x-ray spectrometry (EDS) are now capable of routinely producing ultra-high resolution information, and efforts to produce three dimensional tomograms with a corresponding spectra at each voxel are presently being reported. Automatic segmentation of regions of biological or materials samples is becoming increasingly important as the size and speed of generation of these datasets are quickly exceeding the capability of microscopists to handle them off the microscope.

Perhaps unexpectedly, we thus find that sparse imaging methods have considerable overlap with imaging projects involving extensive and prolonged imaging. Both share, as discussed above, problems with the high dimensionality and large size of data with unclear informational content. Herein, we report preliminary work to address concerns of data management and image/volume analysis with self-organizing neural networks and Bayesian non-parametrics.

In contrast to supervised neural networks, self-organizing and unsupervised neural networks attempt to discover underlying structure in high-dimensional data by mapping this multi-dimensional data to a series of networked nodes [3]. Thus, they may be thought of as a similarity preserving form of dimensionality reduction or clustering. Notably, such methods can perform meaningful dimensionality reduction and clustering without feature indexing or labeling, and have been shown to preserve the topology of the underlying high dimensional space [3].

These maps can be combined with nonparametric clustering methods, in which the number of clusters to group similar data, is learned. Thus, when combined together these tools become a powerful force to explore and extract meaningful information from complicated high dimensional microscopy data sets.
As a demonstration, the usefulness of these methods is explored in producing segmentations from highly under-sampled images (up to 80%) in concert with hierarchical Bayesian inpainting methods, which

have been explored previously[1]. The ability to produce segmentations as a by-product of sparse imaging is an interesting benefit and is demonstrated on fragile biological specimens and *in-situ* aqueous observations in a scanning electron microscope (SEM) [4].

References:

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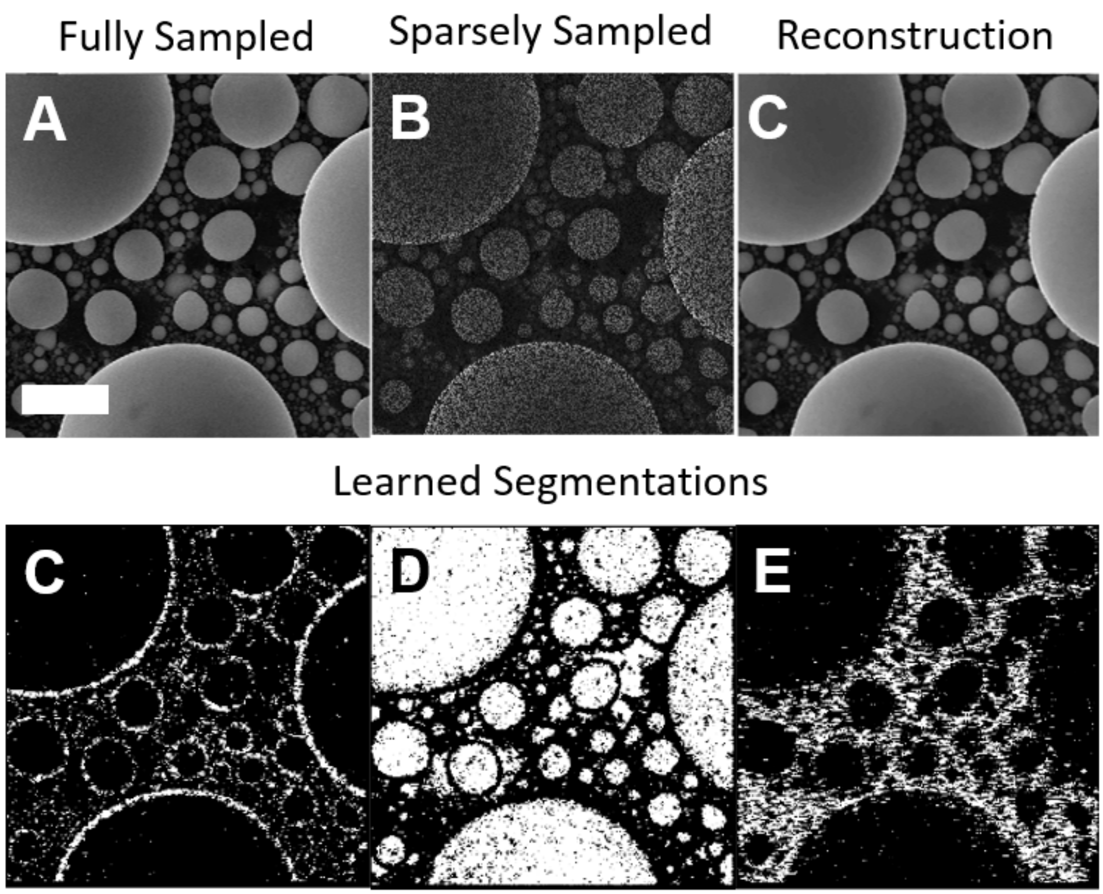

Figure 1. (a) Fully sampled secondary electron image of gold nanoparticles on silicon (scale bar = 250nm). (b) Experimental sparsely sampled image utilizing an electrostatic beam blanker. (c) Reconstructed image utilizing Bayesian dictionary learning. (c-e) Learned segmentations from purely the sparse pixels utilizing self-organizing neural networks and nonparametric clustering.