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Efficient Sampling and Reconstruction Strategies for in-situ SEM/STEM

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Images/spectral maps from scanning (transmission) electron microscopes (S(T)EMs) are now used routinely to quantify the morphology, structure, composition, chemistry, bonding, and optical/electronic properties of nanostructures, interfaces and defects in many materials systems. However, quantitative and reproducible observations for many materials of current technological importance are limited by electron beam damage destroying the sample before the highest resolution information is obtained. The effect of electron dose becomes even more important when we perform in-situ measurements, as the kinetic pathways that we are trying to observe can be completely changed by the beam. The aim for broadening quantitative S(T)EM applications to a wider range of samples and processes is therefore now to focus on the most efficient use of the dose that is supplied to the sample. In practice, this is achieved by minimizing the experimental dose, dose rate and dose overlap for any image, resulting in a controlled dose fractionation that maximizes the data content per unit dose, i.e. reducing the number of pixels being sampled (Figure 1), and using inpainting /machine learning methods to reconstruct the images [1,2].

The key challenge for all sub-sampling methods is of course to be able to accurately reconstruct the sub-sampled image. Compressive sensing and/or Inpainting is a method of efficient signal acquisition and reconstruction by solving of a set of undetermined linear equations [3]. The method relies upon the fact that given an appropriate coordinate system (or 'Dictionary'), complex high dimensional signals can be expressed within a margin of error by a (potentially) much smaller set of parameters, describing a linear combination of signal patterns with their scalar coefficients. As an example of this process, consider the case of a simple 1-D signal, such as the wave shown in Figure 2. A series of dictionary elements (in this case Fourier components) can be used to re-construct a true signal (Figure 2b). Figures 2 c-f show that for relatively high levels of sub-sampling, it is clear that we can fit the dictionary elements to the observation, effectively "inpainting" the missing level of sampling in our experiment. It is relatively straightforward to transfer this approach to a 2-D image obtained from a electron microscope, with Figure 3 showing an example of a reconstruction for an atomic resolution Z-contrast image.

In the presentation, the use of sub-sampled imaging for in-situ experiments will be discussed as a method for controlling the effects of the electron beam in determining the outcome of the experiment. In addition, the potential benefits of the use of sub-sampled image simulations, to generate real time reconstructions for a wide range of hyperspectral images and image analytics will be discussed.

References:

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[3] M. Zhou et al, *IEEE Transactions on Image Processing* **21,** 130-144 (2012)

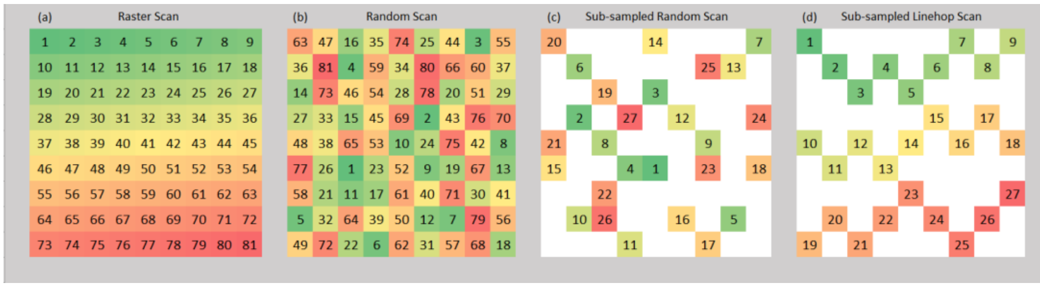

Figure 1: Examples of various scanning patterns: (a) traditional raster scanning. (b) Space filling random scanning, which has been shown to reduce beam damage in beam sensitive samples. (c, d) sub-sampled random scanning and sub-sampled linehop scanning both at 33.3% sampling ratio.

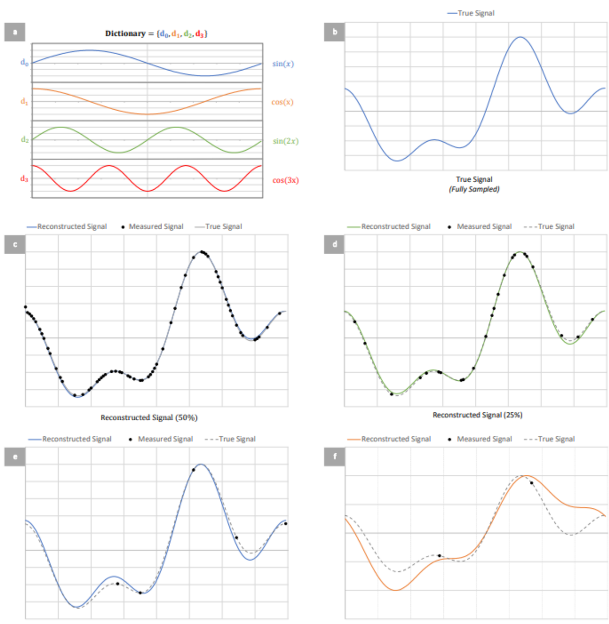

Figure 2: (a) A series of dictionary elements (fourier components) can be combined with defined scalar weightings to reproduce the true signal (b). By reducing the number of points in the true signal (c-f) we can increase the speed and decrease the dose in the sampling of our experiment, but still generate a good fit to the data. At some point (f) the level of sub-sampling leads to an unacceptable error in the reconstruction. This level of sub-sampling is material and instrument dependent [2].

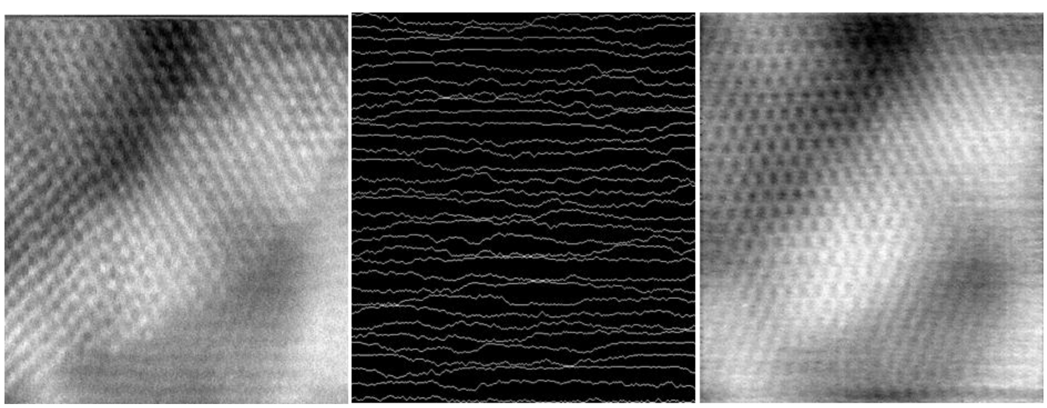

Figure 3: (a) 512 x 512 fully sampled atomic resolution Z-contrast image of Ceria. (b) 6.25% sub-sampled line-hop image acquired with the same beam conditions at the same location and (c) reconstruction of the 6.25% sub-sampled image using BPFA [3].

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