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Under-sampling and Image Reconstruction for Scanning Electron Microscopes

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Electron Microscopes have been used to investigate materials from micron to nano scale. Scanning electron microscopes (SEM) as well as scanning transmission electron microscopes (STEM) can acquire image data relatively fast, however acquiring spectroscopic data requires longer data collection times. Depending on the desired resolution or sample area, this can make a significant difference in the duration and feasibility of the experiment. Moreover, for electron beam sensitive samples, it is necessary to acquire the image data with minimal exposure time as not to further damage the sample [1]. Here, we propose an under-sampling and reconstruction method to reduce the data collection time while maintaining imaging accuracy.

A training dataset consisting of several images with features of interest is initially collected. Small patches of n x n pixels are extracted from this set of images and flattened into a library of column vectors. Each column in the library is normalized by subtracting the mean and dividing by the standard deviation of that column. Singular Value Decomposition (SVD) is then applied on the library and [U S V] matrices are calculated. Left singular vectors of the matrix U becomes our dictionary D, whose columns correspond to the features for image reconstruction.

We use a new test image X which represents the sample to be imaged. P is a measurement mask in which 14% total number of pixels are chosen randomly and set to 1, others 0 [2]. The under-sampled measurement of image patch is then represented by Y = PX. Since we have the measured image patch Y, measurement mask P and dictionary D, the problem is reduced to find sparse coefficient vector W which can best reconstruct a fully sampled image X_r = DW. The reconstructed image is the combination of all reconstructed patches with averaged overlap pixels. The sparse coefficients are calculated by solving the optimization problem using Lasso [3]:

$$argmin_W \left\{ \| Y - PDW \|_2^2 + \lambda \| W \|_1 \right\}$$

The reconstructed image is the multiplication of the dictionary and sparse coefficients. Here, a dictionary is also generated using public available dataset CIFAR-10 [4]. The CIFAR-10 datasets has 60K 32 x 32 images in 10 classes: airplane, automobile, bird, cat, deer, dog, frog, horse, ship and truck. 50 images are randomly selected from the dataset, transformed from RGB to gray-scale and 8 x 8 patches are extracted to form a feature space. This dictionary is considered as unbiased in comparison with previously collected SEM images of the same sample.

We have tested this method using SEM data of milled maize stover for cellulose fibril study [5]. The specimens were attached to an aluminium sample mount using carbon adhesive tabs and coated with 5-10 nm platinum/palladium (80:20) with a Denton DV502 vacuum evaporator. Samples were then examined at 3 kV on a Hitachi S-4800 field emission SEM. These SEM images verified the ~ 100 nm size cellulose fibrous bundles in dried material. We will compare the results of reconstructed images obtained using both biased and unbiased dictionaries, and discuss our efforts towards building image datasets for microstructural characterization. This under-sampling and image reconstruction method can be applied to various modalities of electron microscopes (SEM, TEM, STEM and etc.) and for different material characterization [6].

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[6] The authors acknowledge funding from Laboratory-Directed Research and Development (LDRD) at Argonne National Laboratory. SEM images are collected with Dr. Lee Makowski at Northeastern University.

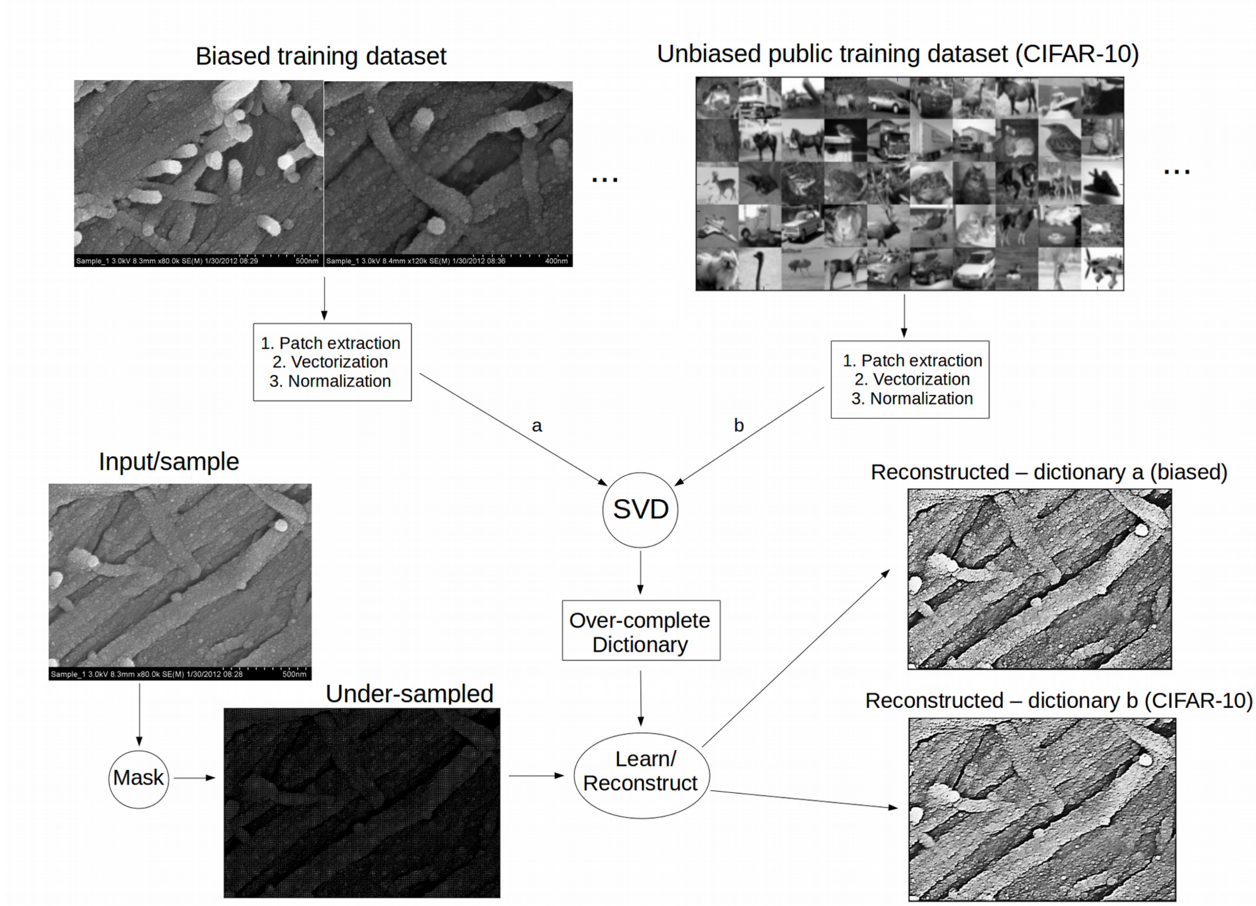

Figure 1. System flow of under-sampling and image reconstruction method. Top left SEM images are previously collected dataset (biased). Top right are randomly selected images from CIFAR-10 public dataset (unbiased). The scale bar of the bottom test SEM image is 500 nm.

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