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Exemplar-Based Inpainting Based on Dictionary Learning for Sparse Scanning Electron Microscopy

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High-throughput scanning electron microscopy (SEM) aims to reduce dose for sensitive specimens as well as reducing acquisition times to be able to acquire large volumes in a meaningful time. Sparse sampling is one key to make such acquisitions possible. We propose a new reconstruction technique for such sparsely sampled SEM data, which is based on exemplar-based inpainting known from image processing [1].

In serial block face scanning electron microscopy a sample is acquired layer by layer. This is achieved by scanning the surface of a specimen voxel by voxel to obtain one two dimensional image. The whole volume is acquired as three dimensional data by consecutively removing thin layers from the surface using a focused ion beam or a mechanical cutter until the whole specimen has been scanned. The bottleneck for recording large three dimensional volumes voxel by voxel is sensor bandwidth and, hence, acquisition time. For a volume of 2048x2048x1024 voxels resolution at a per-voxel dwell time of 20 µs almost one day is needed for solely the data acquisition. Speeding up this acquisition could be achieved by reducing the dwell time, which results in a degradation of signal quality and in noisy images with bad signal-to-noise ratios.

Alternative to conventional scanning techniques that acquire the image row by row on a Cartesian grid, sparse scanning techniques that only scan a small percentage of the whole specimen have gained attention recently. Scanning just a small subset of possible voxel positions can increase the imaging throughput remarkably. The sparsely scanned data must then be processed further to obtain a full resolution image. Applying appropriate reconstruction techniques, a dense volume with minimum loss of information is recovered. The selection of scanning positions for recording the sparse data can be done randomly, as it is usually done for inpainting algorithms inspired by compressive sensing. If additional knowledge on the structure of the specimen is available, adaptive sampling schemes can provide superior results [2].

Exemplar-based inpainting is a class of inpainting algorithms that originates from the field of image processing. The main goal of these methods is removing objects in images or restoring damaged portions of an image by inserting information from the surroundings. More specifically, the values of the missing region are modified such that the inserted part is visually indistinguishable from its surroundings. Adapting this idea, we developed a three dimensional inpainting method [3] that inserts missing voxels with the help of prior knowledge. Instead of using the surroundings of missing voxels, a so called dictionary is trained based on full scans of the image domain to be reconstructed. The dictionary contains a large number of image patches of a predefined size. Missing voxels are then reconstructed iteratively by inserting whole patches. The procedure starts by identifying a region in the sparse image where a patch should be inpainted. The known voxels in that patch are then used to find the patch in the dictionary that fits best. This fitting is performed by means of a cost function, for example the L_2-norm of known voxels. The missing voxels are then inserted into the sparse image. This is repeated until the whole image has been reconstructed.

The algorithm was tested on an image that was reduced down to 20% of its content. Using Bernoulli sampling and a data specific dictionary of the original dataset, which did not include the image to be reconstructed, we were able to reconstruct the image while preserving the visual quality (Figure 1). This will open the possibility to reduce acquisition times of big volumes [4].

References:
[1] A. Criminisi *et al,* IEEE Transaction on Image Processing **13(9)** (2004) p. 1200.
[2] T. Dahmen *et al,* Sci. Rep. (2016), Article number 25350.
[3] P. Trampert *et al,* Microscopy and Microanalysis **22(S3)** (2016), p. 554.
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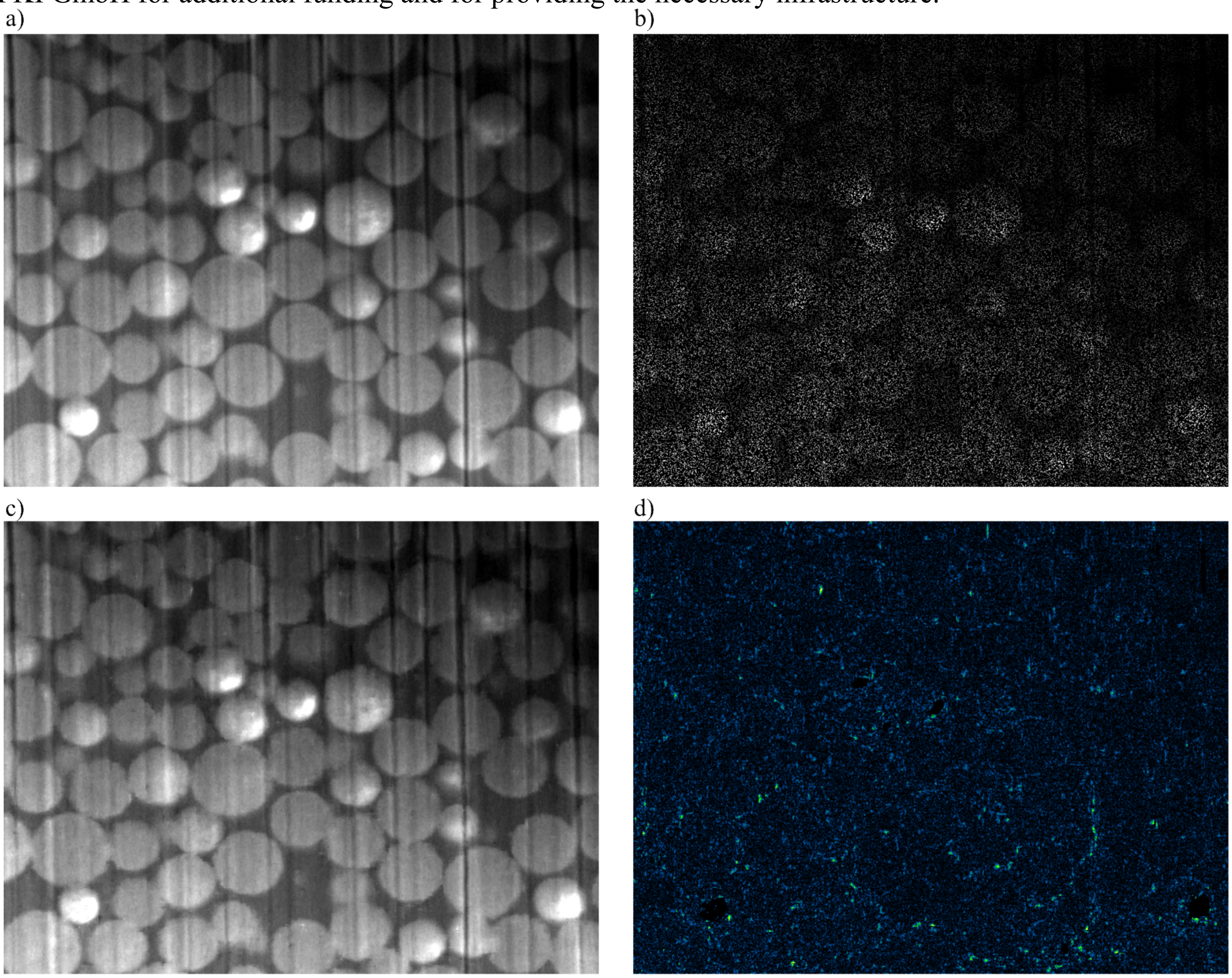

Figure 1. Silica micro balls sample. a) Ground truth image, b) 20% of original image sampled randomly using Bernoulli sampling, c) Reconstructed image with exemplar-based inpainting and data specific dictionary, and d) Differences between ground truth and reconstruction resulting in a PSNR of 31.87.

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