doi:10.1017/S1431927622011011
Microsc. Microanal. 28 (Suppl 1), 2022

Approaching *Real-Time* Low-Dose STEM: Image Recovery from Subsampled Measurements via Online Bayesian Dictionary Learning

J. Wells[1*], D. Nicholls[2], A.W. Robinson[2], A. Moshtaghpour[2,3], Y. Zheng[4], J. Castagna[5], and N. D. Browning [2,6,7]

[1.] Distributed Algorithms CDT, University of Liverpool, Liverpool, L69 3GH, UK.
[2.] Mechanical, Materials, & Aerospace Engineering, University of Liverpool, Liverpool, L69 3GH, UK.
[3.] Rosalind Franklin Institute, Harwell Science & Innovation Campus, Didcot, OX11 0QS, UK.
[4.] Department of Eye and Vision Science, University of Liverpool, Liverpool, L7 8TX, UK.
[5.] UKRI-STFC Hartree Centre, Daresbury Laboratory, Warrington, WA4 4AD, United Kingdom
[6.] Physical & Computational Science, Pacific Northwest National Lab, Richland, WA 99352, USA.
[7.] Sivananthan Laboratories, 590 Territorial Drive, Bolingbrook, IL 60440, USA.
Corresponding Author: J. Wells (sgjwells@liverpool.ac.uk)

In recent years, various Compressive Sensing (CS) approaches have been applied to Scanning Transmission Electron Microscopy (STEM) images [1-3], demonstrating that subsampled image acquisition, accompanied by an appropriate method of inpainting the missing pixel information, provides an alternative method for achieving low-dose STEM and imaging beam-sensitive materials [4]. A full image inpainting algorithm (taking only a subsampled measurement as its input) typically consists of a blind dictionary learning algorithm such as Beta-Process Factor Analysis (BPFA) (developed in [5]) which learns the representative patterns within the target image, followed by a sparse-coding algorithm which aims to find the optimum combination of the learned dictionary 'elements' to best represent each overlapping patch of the image provided in the target batch. These methods, however, are usually very computationally expensive, meaning that time-to-solution for even reasonably small greyscale images such as [512x512] range from 5-10 mins depending on the input parameters [3], and for larger images will easily reach multiple hours when operating in *serial*. While this is acceptable for post-acquisition STEM image analysis, such as generating a final (optimum) reconstruction from a previously acquired subsampled scan, these reconstruction times are prohibitively long for *real-time* operation and calibration of an electron microscope; something which is crucial for any successful real-life application of low-dose CS-STEM. In addition to a lengthy time-to-solution for reconstructing subsampled images, many implementations of Bayesian dictionary learning and reconstruction require vast amounts of RAM, requiring the storage of a total number of pixel values hundreds of times the total size (area) of the target image, due to pixel information being duplicated many times over in memory; for larger (e.g. 4k) images this can quickly exceed the amount of memory available on a typical consumer device/workstation.

One way to speed up reconstructions is to take advantage of the independent nature of many of the steps that need to be performed throughout the dictionary learning and sparse-coding process. In both cases, a separate algorithm is performed for each dictionary element or overlapping signal (2D patch) in the given batch respectively, making the process highly parallelizable. By developing a method for generating batches of target signals (patches) from an image *on-demand* (rather than attempting to build a full matrix of all overlapping signals), the amount of RAM required can be drastically reduced, and time-to-solution decreased further due to less time spent creating and copying memory. Additionally, this gives us the ability to determine new strategies for choosing the locations (within the target image) to sample signals from in the next batch, perhaps adjusting the sampling strategy *on-the-fly* to target the most important regions of the image, or 'covering' the total image area in a much more efficient way,

avoiding re-encoding pixels which are already sufficiently recovered, and resulting in even faster reconstructions. Finally, unlike existing methods where the image is only available when the full recovery process is finished, our method enables live/online inspection of image recovery and early halting by the user when a sufficient quality of reconstruction has been reached. *Figure 1* showcases the results of this implementation applied to a (STEM) image of high-resolution Ceria, showing the input image (subsampled to 25%), the 'live' reconstruction at Batches 6 and 56 (after ~1s and ~10s respectively), as well as the (fully-sampled) reference image / ground truth. As shown in *Figure 2*, while the inpainting method may be continued for *many* iterations, the relative improvements in Peak Signal-To-Noise Ratio (PSNR) fall extremely quickly, with the majority of the '*useful information*' (such as, in this case, the resolving of atomic columns) being adequately recovered in the first 10 seconds. This significant speed improvement from a range of minutes/hours down to a matter of seconds provides a pathway to *real-time* reconstructions of subsampled STEM images and/or each frame of a live feed from an electron microscope, allowing the operator to preview a beam-sensitive sample under low-dose (subsampled) conditions and make appropriate adjustments to position and focus before acquiring a final (subsampled) scan. While currently implemented in parallel on a CPU, this implementation lends itself well to being performed on a high-performance GPU to reach even faster speeds and enable true *real-time* CS-STEM (frame-by-frame) video reconstruction [6].

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[6] The authors acknowledge funding from ESPRC and Sivananthan Laboratories, IL USA. Dr. Mounib Bahri (University of Liverpool, Liverpool) and Daniel Nicholls[2] are recognized for their work in acquiring data used in *Figure 1*.

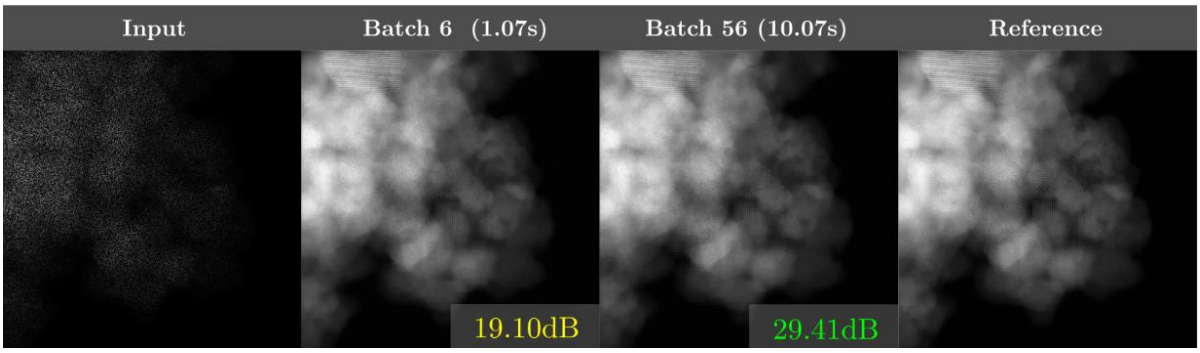

Figure 1: Reconstruction results for a [1024x1024] STEM image of high-resolution Ceria showing the result and PSNR metric at Batch 6 (after ~1 second) and Batch 56 (after ~10 seconds) as well as the (fully sampled) reference image

https://doi.org/10.1017/S1431927622011011 Published online by Cambridge University Press

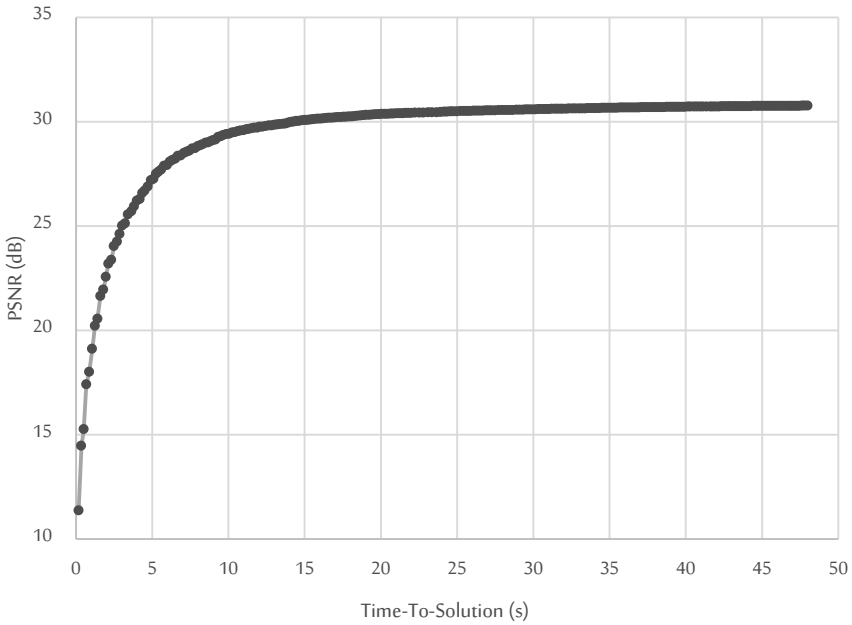

Figure 2: Reconstruction quality (as measured here by PSNR) after each mini-batch (plotted here against time-to-solution at the end of each batch) for the STEM image of Ceria shown above (in *Figure 1*).

All computation was performed in parallel via a shared memory paradigm on an Intel Xeon E5-2678 v3 CPU with 24 threads.

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