doi:10.1017/S1431927616011260
Microsc. Microanal. 22 (Suppl 3), 2016

Compressive Sensing in Microscopy: a Tutorial

Andrew Stevens[1,2], Hao Yang[3], Libor Kovarik[1], Xin Yuan[4], Quentin Ramasse[5], Patricia Abellan[5], Yunchen Pu[2], Lawrence Carin[2], and Nigel D. Browning[1]

[1.] Pacific Northwest National Laboratory, Richland USA
[2.] Duke University, ECE, Durham USA
[3.] Lawrence Berkeley National Laboratory, Berkeley USA
[4.] Bell Laboratories, Murray Hill USA
[5.] SuperSTEM, STFC Daresbury Laboratories, Warrington UK

Currently many types of microscopy are limited, in terms of spatial and temporal resolution, by hardware (*e.g.*, camera framerate, data transfer rate, data storage capacity). The obvious approach to solve the resolution problem is to develop better hardware. An alternative solution, which additionally benefits from improved hardware, is to apply *compressive sensing* (CS) [1]. CS approaches have been shown to reduce dose by as much as 90% in electron microscopy [2, 3, 4]. Optical imaging and microscopy have also seen substantial benefits [5, 6, 7, 8, 9, 10, 11, 12, 13].

This tutorial will briefly introduce the principles of CS. Primarily, we will focus on the setup and modifications necessary for applying CS to a few different types of microscopy and spectroscopy (*e.g.*, STEM [2], EELS, TEM-video [3], optical-video [7]). We will show results from these compressive microscopy approaches. Moreover, an approach for detecting CS reconstruction errors (*i.e.*, errors introduced by the image processing algorithm) will be discussed.

Two examples are shown in Figure 1. The first example shows a 10:1 compression of video transmission electron (TEM) microscopy data. The second example shows the reconstruction of a scanning TEM (STEM) image using only 20% of the pixels [14].

References:

[1] RG Baraniuk. IEEE signal processing magazine **24(4)**.
[2] A Stevens, H Yang, L Carin *et al.* Microscopy **63(1)**, (2014), pp. 41.
[3] A Stevens, L Kovarik, P Abellan *et al.* Advanced Structural and Chemical Imaging **1(1)**, (2015), pp. 1.
[4] A Stevens, L Kovarik, P Abellan *et al.* Microscopy and Microanalysis **21(S3)**, (2015), pp. 1583.
[5] M Zhou, H Chen, J Paisley *et al.* Image Processing, IEEE Transactions on **21(1)**, (2012), pp. 130.
[6] Z Xing, M Zhou, A Castrodad *et al.* SIAM Journal on Imaging Sciences **5(1)**, (2012), pp. 33.
[7] X Yuan and S Pang. Biomedical Optics Express **7(3)**, (2016), pp. 746.
[8] Y Pu, X Yuan and L Carin. arXiv:14126039 .
[9] Y Pu, X Yuan, A Stevens *et al.* In AISTATS 2016.
[10] P Llull, X Liao, X Yuan *et al.* Optics Express **21(9)**, (2013), pp. 10526.
[11] X Yuan, J Yang, P Llull *et al.* In ICIP 2013 (IEEE).
[12] J Yang, X Yuan, X Liao *et al.* Image Processing, IEEE Transactions on **23(11)**, (2014), pp. 4863.
[13] X Yuan, P Llull, X Liao *et al.* In CVPR 2014 (IEEE).
[14] This work was supported in part by US DOE Grant No. DE-FG02-03ER46057. This research is also part of the Chemical Imaging Initiative conducted under the LDRD Program at PNNL and used EMSL, a national scientific user facility sponsored by the DOE Office of Bio & Env. Research at PNNL. PNNL is a multi-program national lab operated by Battelle Memorial Institute under Contract DE-AC05-76RL01830 for the US DOE.

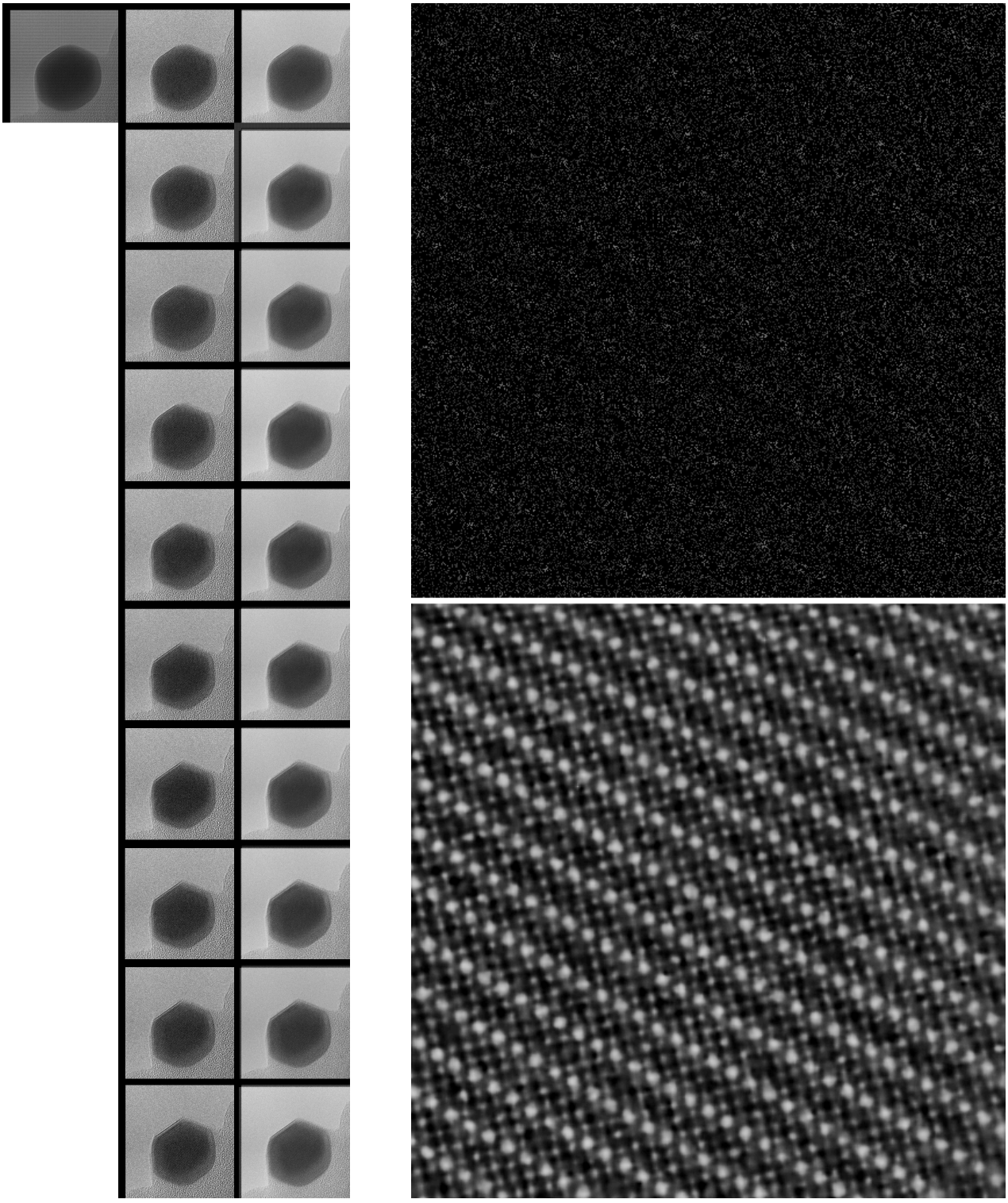

Figure 1: *Left*: An illustration of CS-TEM with 10 video frames compressed into 1 (simulated). The top left image shows the compressed frame, the middle column of images shows the reconstructed frames, and the right column shows the original frames. *Right*: An example of CS-STEM with 80% of the pixels missing at random (experimental). The top image is the acquired data, and the bottom image is the CS reconstruction.

https://doi.org/10.1017/S1431927616011260 Published online by Cambridge University Press