

Recent Advances in Electron Tomography and Applications in the Semiconductor Industry

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INTRODUCTION

As device architectures become increasingly complex and heterogeneous, advanced three-dimensional (3D) characterization tools are needed to elucidate structure-property relationships and optimize process conditions. At the nanoscale, high-angle annular dark-field scanning transmission electron microscope (STEM-HAADF) tomography is widely used for 3D morphological analysis of semiconductor devices [1]. This technique consists in acquiring a series of 2D STEM-HAADF projections at different viewing angles, and applying a dedicated algorithm to retrieve the 3D morphology of the object.

3D chemical imaging of nanodevices is nowadays possible by energy-dispersive x-ray spectroscopy STEM (STEM-EDX) tomography, which has benefited greatly from recent developments in electron sources such as the 'X'-FEG (Field Emission Gun), and multiple X-ray detector systems such as the Super-X, incorporating four SSD (Silicon Drift Detectors) detectors [2]. The technique remains however very time-consuming, and reduced X-ray count rate and number of projections are necessary to minimize the total acquisition time and avoid beam damage during the experiment. In addition, tomographic series of STEM-EDX datacubes are too large to be analyzed by commercial software packages in an optimal way. In order to make STEM-EDX tomography accessible to the semiconductor industry, it is necessary to automate the data processing and employ sophisticated methods capable of producing high quality reconstructions from a limited number of noisy projections.

In this presentation, we will give an overview of the recent advances in electron tomography, with an emphasis on STEM-EDX tomography and the processing tools necessary for accessing reliable 3D information. We will show that multivariate statistical analysis methods [3] can be used for unsupervised identification of chemical phases, while automated elemental analysis of very noisy EDX-STEM datasets can be achieved by principal component analysis (PCA) followed by Gaussian curve-fitting methods.

We will also illustrate the superior performance of compressed sensing (CS) approaches [4,5] compared to classical tomographic algorithms, for 3D reconstructions from highly under-sampled datasets.

As an example, we show below the 3D chemical analysis of an arsenic-doped silicon structure for fin field-effect transistor (FinFET) technology [6]. Other applications of electron tomography for the 3D analysis of semiconductor devices and materials will be presented, ranging from phase-change materials [5] to DNA origami nanostructures for silicon patterning. Prospects of deep learning approaches for spectral analysis and tomographic reconstruction will be also discussed.

3D CHEMICAL ANALYSIS OF AN ARSENIC-DOPED SILICON STRUCTURE

The investigated sample is a Si fin-shaped structure doped with As as an n-type dopant. The structures were fabricated on a 300 mm Si-on-insulator substrate with top Si and buried oxide thicknesses of 14 nm and 25 nm. A Si epitaxy process was then performed to obtain the targeted total Si layer of 60 nm. This top-Si layer was patterned using e-beam lithography and dry etching to obtain fin-like structures with 45 nm width. Samples were then doped by plasma immersion ion implantation using AsH₃ gas as As precursor and encapsulated in

SiO_x. A needle-shaped sample was prepared by focused ion beam, and inserted in a Thermo Fisher Scientific Titan Themis operating at 200 kV and equipped with a probe corrector and a Super-X EDX system. 21 STEM-EDX projections were acquired between -90° and +90°, mainly every 10°.

Hyperspy [7], a Python-based software for hyperspectral data processing, was used to batch-process the STEM-EDX tomographic dataset. Non-negative matrix factorization (NMF) was applied to decompose the dataset into spectral signatures and loading maps, both of which are constrained to be non-negative. The number of components to use for the factorization was determined following the scree-plot inflexion point of the principal component analysis (PCA), leading to the identification of three chemical phases in the sample: Si, SiO_x and As (Figure 1).

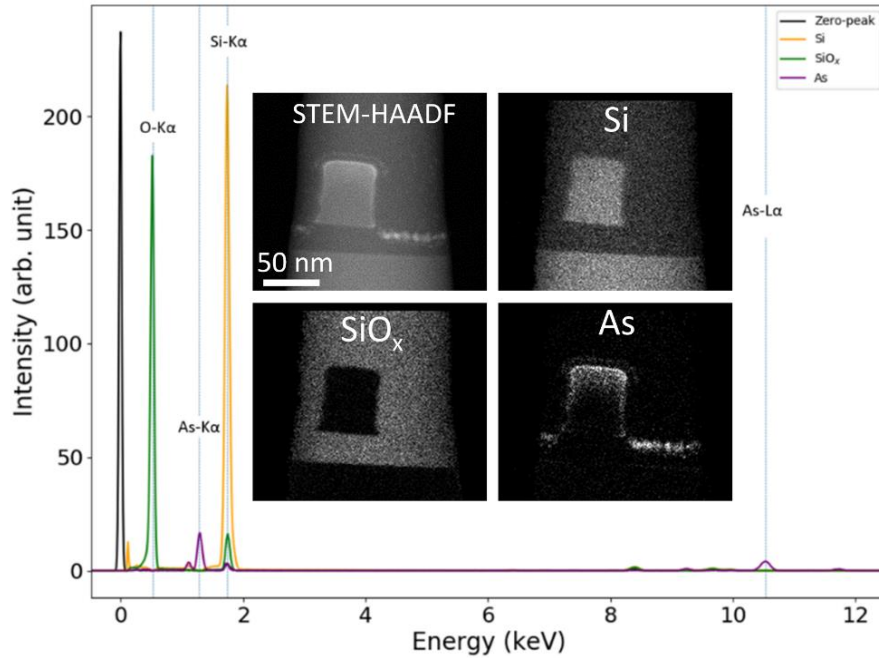


FIGURE 1. Spectral components (Si, SiO_x and As) obtained from NMF decomposition of the STEM-EDX dataset composed of 21 datacubes. The insets correspond to the STEM-HAADF projection and Si, SiO_x and As maps at 5° tilt angle. Adapted from [6].

The tomographic reconstructions were performed using Pysap-etomo [5,8], an in-house Python library dedicated to CS approaches for electron tomography. In the present example, total variation minimization (TV) [4] was employed to reduce the artefacts due to the limited number of projections and the noisy signal. Figure 2(a) shows the volume rendering of the tomographic reconstructions of Si (orange), SiO_x (green) and As (purple) chemical phases. Figure 2(b)–(d) are xz slices through the reconstruction of Si, SiO_x and As volumes. A line profile through the central xz slice (arrow in figure 2(e)) indicates implantation of ~20 nm inside the Si structure.

Note that TV promotes piecewise constant structures even when there is a gradual change in intensities. As a result, stair-case and patchy artefacts may appear in the non-piecewise constant regions. We will show that these artefacts can be reduced using higher-order derivative methods or wavelet-based CS algorithms implemented in Pysap-etomo [5,8].

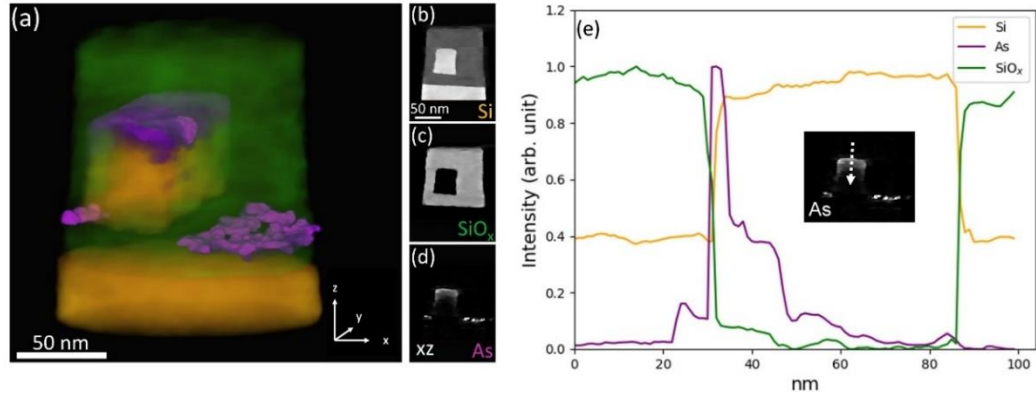


FIGURE 2. (a) Volume rendering of the tomographic reconstructions of Si (orange), SiO_x (green) and As (purple) chemical phases; (b)–(d) *xz* slices through the reconstruction of Si, SiO_x and As volumes; (e) a depth profile through the fin-shaped structure on a selected section (dotted arrow in the insert), after normalization of the three volumes. Adapted from [6].

The tools presented are also applicable to other spectroscopic modes such as electron energy loss spectroscopy STEM (STEM-EELS) [5] or simultaneous STEM-EELS/EDX, and recent studies have shown that correlative approaches combining analytical electron tomography with other techniques (e.g. STEM-HAADF tomography or atom probe tomography (APT) [9]) have the potential to provide a more complete knowledge about the nanostructures [10].

REFERENCES

1. C. Kübel et al., *Microsc. Microanal.* **11**(5), 378-400 (2005).
2. S.M. Collins and P.A. Midgley, *Ultramicroscopy* **180**, 133-141 (2017).
3. M. Shiga et al., *Ultramicroscopy* **170**, 43-59 (2016).
4. Z. Saghi et al., *Nano Lett.* **11**(11), 4666-4673 (2011).
5. M. Jacob et al., *Ultramicroscopy* **225**, 113289 (2021).
6. M. Jacob et al., *Semicond. Sci. Technol.* **36**, 035006 (2021).
7. <https://doi.org/10.5281/zenodo.5608741>
8. <https://github.com/CEA-COSMIC/pysap-etomo>
9. W. Guo et al., *Microsc. Microanal.* **22**, 1251-1260 (2016).
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KEYWORDS

3D analysis, electron tomography, morphology, chemical composition, compressed sensing, machine learning.