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Automated Background Subtraction Technique for Electron Energy-loss Spectroscopy and Application to Semiconductor Heterostructures

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EELS quantification, background subtraction, ionization edge, core-loss, hyperspectral imaging

Summary

Electron energy loss spectroscopy (EELS) has become a standard tool for identification and sometimes also quantification of elements in materials science. This is important for understanding the chemical and/or structural composition of processed materials. In EELS, the background is often modelled using an inverse power-law function. Core-loss ionization edges are superimposed on top of the dominating background, making it difficult to quantify their intensities. The inverse power-law has to be modelled for each pre-edge region of the ionization edges in the spectrum individually rather than for the entire spectrum. To achieve this, the pre-requisite is that one knows all core-losses possibly present. The aim of this study is to automatically detect core-loss edges, model the background and extract quantitative elemental maps and profiles of EELS, based on several EELS spectrum images (EELS SI) without any prior knowledge of the material. The algorithm provides elemental maps and concentration profiles by making smart decisions in selecting pre-edge regions and integration ranges. The results of the quantification for a semiconductor thin film heterostructure show high chemical sensitivity, reasonable group III/V intensity ratios but also quantification issues when narrow integration windows are used without deconvolution.

Introduction

Electron energy-loss spectroscopy (EELS) can be used for identification and quantification of light elements present in a material at near atomic or even atomic resolution. An EEL spectrum consists of a zero-loss peak, band-edge transitions, plasmon and ionization edges on top of a background which decays almost exponentially with energy for high energy-losses. The ionization core-losses superimposed on this can be extracted using statistical tools (Egerton, 1975, 2011b). However, the inverse power-law fails to model EELS in the low-loss region (van Puymbroeck et al, 1992). The conventional method of quantification by manually selecting a pre-edge region to extract ionization edges is exhaustive and leads to inconsistency for thousands of spectra. State of the art software tools like Hyperspy (de la Peña et al., 2015) and Gatan Digital Micrograph (Gatan, 2015) remove such inconsistency partly by applying quantification routines to entire EELS SI data sets. Similarly, a model-based approach to EELS quantification has been presented (Verbeeck & Van Aert, 2004).

These authors later discussed standard-less quantification of EELS, which provided better results (Verbeeck & Bertoni, 2008). None of these software packages, however, [detects an ionization edge and quantifies it automatically without any human intervention: Hyperspy can perform an independent component analysis \(de la Pena, 2011\) but the physical interpretation of the statistically significant components in terms of element-specific core losses still needs to be provided by the user for any type of multivariate statistical analysis \(Walther and Trebbia, 1996\). Digital Micrograph scripts such as Oxide Wizard \(Yedra et al., 2014\) typically work on the basis of the user first assigning regions of interest and identifying edges manually, which the algorithm can then track and quantify in similar spectra of larger data sets.](#) The aim of this study is to subtract the EELS background and provide elemental maps and profiles of thousands of spectra or an extended SI without any prior knowledge of the ionization edges.

Description of the program

The process can be explained in two parts: ionization core-loss edge detection and background subtraction for detected individual ionization edges. The quantification of EELS used in our approach is by the standard integration method (Egerton, 1978). To quantify a spectrum there are a lot of challenges in terms of artifacts, noise and gain correction problems of the charged couple device (CCD) camera. Hence, a pre-treatment of spectra is necessary before the process of edge detection and background subtraction. If the background is exponentially decaying, there is no ionization edge and the signal-to-noise-ratio (SNR) is high, then the gradient of the spectrum should be negative everywhere. As the spectrum is pre-processed, positive gradients indicate the presence of core-loss edges. A look-up table is used to accurately identify the corresponding core-losses of the elements. An inverse power-law is used to fit a curve in the pre-edge region to subtract the background. The extracted core-loss edges are used for further quantification using integration after background subtraction. [All programming was performed in Matlab using the current version, R2015b.](#)

Data pre-processing

The noise in a spectrum arises due to a combination of low electron count numbers and read-out noise of the CCD camera (Ishizuka, 1993). The objective is to detect the core-loss edges after the acquisition of the spectrum image in the presence of noise. The noise in the spectra is a mixture of Poisson noise (or shot noise) and Gaussian noise (de la Pena, 2010). The ionization cross-section decreases with increasing energy loss. As the signal-to-noise-ratio (SNR) decreases with energy-loss, the intensity of high-loss ionization edges becomes comparable to the noise level. This emphasises the necessity of pre-processing signals before calculating the gradient of the spectra. An averaging filter is always inefficient (Boyle & Thomas, 1988; Davies, 1997; Justusson, 1981) as it does not consider the type of noise and spikes (or pulses) are not completely removed (Figure 1). The number of spectral channels selected as filter width, w , influences the residual noise after smoothing but will also suppress the core-loss signal to some degree, in particular for sharp edges. An [averaging](#) filter gives good noise suppression when multiple spectra are averaged, providing a collective representative spectrum with reduced noise. [Principle component analysis \(PCA\) is a form of multivariate analysis, using orthogonal eigenfunctions](#) (Fukunaga, 1990; Jolliffe,

2002; Pearson, 1901; Manly, 2004). A multivariate analysis tool (simply called PCA function in Matlab R2015b) has been used to analyse datasets in an unsupervised manner. The dataset in this case is the SI. The components of the PCA are spectral components ranked in order of significance. The lower order components with high variance represent all the components needed to describe most features of the spectrum apart from the noise (low variance). Hence, PCA can in principle be used for denoising the spectrum, and a Poisson-weighted PCA algorithm that properly accounts for the variance in shot noise has been used to reduce noise in Time-of-Flight Secondary Ion Mass Spectrum images (Keenan and Kotula, 2004). If the noise is Poissonian however, a morphological filter such as a median filter is the most effective way of improving the SNR, as shown in Figure 1. In 2-D (images), a median filter has been proven to be best filter in case of 'salt and pepper noise', which corresponds to Poisson noise in images (Lim, 1990; Pratt, 2007). Here, it preserves the shape of the spectrum. Figure 1 shows the performance of different filters in terms of removing artificial spikes in a spectrum with a delayed In M-edge from InGaAs. As the SNR is decreasing with energy almost exponentially, a median filter is chosen as defined in equation (1).

$$S' = \exp\{\text{median}(\ln(S))_w\} \quad (1)$$

where S is the spectrum, w is a window over which the median filter is applied. In the following, all spectra were median filtered first to help identify the core-loss edges, then the quantification routines for background fit, extrapolation and signal integration were applied to the unfiltered spectra. Filtering will not remove noise due to CCD gain inconsistencies. This can lead to false positive identification of apparent ionization edges.

Insert Figure 1 about here

Detection of ionization core-loss edges

For automation of background subtraction, a novel approach of core-loss edge detection is proposed. The gradient of the EELS SI in the direction of energy-loss is determined by equation (2).

$$\nabla SI = \frac{\partial SI}{\partial E} \hat{E} \quad (2)$$

where ∇SI is the gradient of the SI (data cube) with regard to spatial \hat{x} , \hat{y} directions and energy-loss direction \hat{E} . The gradient of EELS has to be negative for ranges beyond multiple plasmon losses and without any core-losses. The only points that are positive must be due to the presence of noise or ionization edges. If the EELS SI is de-noised, the probability of positive gradient being noise is low, although clearly dependent on the type of denoising method used. The angle (θ) between the EELS and horizontal energy axis is determined by equation (3) and can be plotted, as shown for an example spectrum of silicon with carbon in Figure 2.

Insert Figure 2 about here

$$\theta = \arctan(\nabla SI) \hat{E} \quad (3)$$

Only positive angles are considered further as negative values are due to the background of EELS. A cluster of positive angles is formed if a core-loss edge is present. Positive angle values without a cluster are due to noise. Clusters are detected by counting the positive

angular data points that are comparable to the size of a window. **The flow chart for the process implemented in Matlab is shown in Figure 3.**

Insert Figure 3 about here

The size of the window is chosen such that it should be comparable to the sharpness of the onset of typical edges (a few eV for sharp hydrogenic and up to 10eV for delayed edges). Similarly, the window size should not be too small (<5 channels), to avoid false positives due to noise. Typically, the window sizes selected are between 5 to 20 channels wide (**the default is $w=15$**), and clusters are identified as intervals of that given width wherein at least 2/3 of all channels have angular values $\theta > 0$.

Due to near edge structures or/and chemical shifts the edges detected may not be at the exact location of the ionization onset predicted for free atoms. It may also happen that 2 or 3 consecutive windows might detect positive angles. To refine the results from ionization edge identification, a look-up table is used containing onset values of all major ionization edges (Ahn et al, 1983; Egerton, 2011b). The shape of the edges is also considered during quantification, as discussed later. The exact edge onset is identified from the predicted edges (clusters) by finding the nearest ionization edge in the look-up table, as shown in equation (4):

$$Edge_i = E_{(\min \|E_n - Cluster_i\|_1)} \quad (4)$$

where E_n is the list of all n ionization edges from the look up table, $Cluster_i$ is the list of all predicted ionization edge onsets (numbered consecutively by index). The ionization edge detection and correction can be visualized as shown in Figure 4.

Insert Figure 4 about here

Histograms of the detected edges in three different EELS SI of a cross-sectioned multi-junction solar cell are shown in Figure 5. While edge onset identification may fail in individual spectra due to noise the histograms clearly show that the identification of the edges is unambiguous when thousands of spectra from all locations in SI are considered. The efficiency of the edge detection is also dependent on the quality of the gain correction **of the CCD. Long exposures** of the zero-loss peak might yield artifacts in successively acquired spectra due to gain changes induced by over exposures. This could potentially lead to false positive detection of ionization edges in EELS acquired with energy offsets. Such artifacts can, however, be identified by varying the energy offset as they remain fixed at that channel (usually around # 100) where the zero-loss peak had been before.

Insert Figure 5: about here

Curve-fitting

The presence of the zero-loss peak and plasmon losses in low loss spectra makes it difficult to model the background for energies below about 100eV. The inverse power-law is used to

model the background in pre-edge regions for individual ionization core-loss edges above this threshold. This may be justified in our case as Table 1 demonstrates we have generally used high dispersions for lower energy losses and lower dispersions at higher offsets so that wide regions with low energy losses, wherein the shape of the core-loss background often departs significantly from the slope expected from a simple inverse power-law function (Leapman, 2005), have been avoided. A linear model of ionization edges superimposed on a background modelled by an inverse power-law at higher losses is considered as shown in equation (5).

$$\text{Spectrum} = AE^{-r} + \sum_{i,j} I_i \sigma_{i,j} \quad (5)$$

where A and r are the inverse power-law curve fitting parameters for energy-loss (E), I is the intensity and σ the ionization cross-section for the j^{th} shell of i^{th} element in the spectrum.

The pre-edge regions for the background modelling should be selected as large as possible to minimize systematic errors. A larger pre-edge region provides more data points for modelling of the background and chemical shifts that could shift the edge onset by up to $\sim 8\text{eV}$ are less prone to influence the background modelling. Due to the possible presence of near edge structure, the pre-edge region should ideally end well before the edge onset. Hence the pre-edge region is selected dynamically by the algorithm over all the core-loss edges and across the EELS SI. The pre-edge region extends typically from half the distance between two consecutive core-loss edges to a few channels before the nominal edge onset.

Standard integration methods are used for the quantification of background subtracted EEL spectra (Egerton, 1978). If the integration window exceeded the experimental energy-loss axis limit then the edge would be omitted (in the semiconductor multilayer example presented later, the integration window for the P L_3 edge was manually reduced to 37.4eV to avoid this). The selection of integration window and the systematic and statistical errors influencing quantification have been discussed by Leapman (2005). Two core-loss edges close to each other will be partially overlapping and are not accurately quantifiable by this integration method. The accuracy of the quantification also depends on the shape of the ionization edges. If the onset of an ionization edge is delayed, small integration windows give high statistical errors. Hence the initially specified integration window (Δ) is applied only to hydrogenic edges. In case of delayed edge onsets, the spectrum is integrated up to the next ionization edge onset, providing better statistics for delayed maximum edge shapes but at the cost of slightly higher systematic errors. EELS is usually performed with a spectrometer entrance aperture, and the integration of the spectrum intensity is a function of collection angle (β) and integration window (Δ) (Egerton, 2011b). The values of partial cross-sections are evaluated from the SIGMAK3, SIGMAL3 and SIGPAR Matlab routines written by Egerton (2011a). The overall process of core-loss edge selection and background subtraction is shown in the form of a block diagram in Figure 6.

Insert Figure 6 about here

Experimental

Four EELS SI using different energy offsets and dispersions were acquired from the same area of a cross-sectioned semiconductor heterostructure designed to be used for multi-junction solar cells. On top of a germanium substrate (not shown due to limited field of

view) several GaAs-based layers of different thicknesses had been deposited. The SIs have been acquired in a JEOL 2010F field emission transmission electron microscope operated in STEM mode at 197kV and equipped with a Gatan Imaging Filter (GIF200) with parameters as shown in Table 1. Figure 7(a) is an annular dark-field (ADF) overview image of the heterostructure obtained with 55-170 mrad collection angle in which the spectrum image and spatial drift regions used are indicated. The SI shows 8 distinctive regions as labelled in Figure 7(b). The thicker layers labelled by numbers 3, 5 and 8 clearly differ in their scattering power due to their different chemistry, which we want to investigate in this study, and the top regions (1 & 2) consist of nano-crystals that appear to overlap in projection or are sintered together and were deposited to further improve the coupling to the incoming light.

	EELS SI_0	EELS SI_1	EELS SI_2	EELS SI_3
SI size [pixels]	90 x 44 x 1024	45 x 22 x 1024	90 x 44 x 1024	92 x 43 x 1024
real-space pixel size [nm]	24.4	48.8	24.4	23.9
dispersion [eV/channel]	0.2	0.1	0.5	1
nominal magnification	20000	20000	20000	20000
conv. angle (α) [mrad]	16.6	16.6	16.6	16.6
coll. angle (β) [mrad]	15	15	15	15
spectrum offset [eV]	0	80	250	950
exposure time [sec]	0.1	0.5	0.5	2
total acquisition time [min]	9	11	44	176

Table 1: EELS data acquisition parameters for the four spectrum images (SI) acquired from the same area, indicated by the green rectangle in Figure 6(a). Actual acquisition commenced in reverse order, starting with the highest energy losses. The SI sizes give pixel numbers along x- and y-directions and channel number along the energy-loss coordinate. Acceleration voltage: 197kV

Insert Figure 7 about here

Results from a test case of a semiconductor heterostructure

Sum spectra are extracted from each individual region for quantification. Elemental concentrations (x) are calculated using equation (6a) where the constant is chosen such that the concentrations of all detected elements sums up to unity in equation (6b).

Quantification results for each region are shown in Table 2. Specimen thickness (t) values in terms of multiples of the mean free path (λ) of inelastic scattering can be extracted from the first EELS SI which contains the zero loss and plasmon peaks. These t/λ values are approximately 1 (except in the top thin layer of region 1) indicating an average specimen thickness around $t \approx 130\text{nm}$, which corresponds to the inelastic mean free path calculated according to Egerton (2011b) for GaAs under the conditions listed in Table 1.

The values in Table 2 are normalised with respect to thickness (t/λ) and exposure time (τ). The parameters in Table 1 are used for the calculation of partial cross-sections, $\sigma(\beta, \Delta)$,

using SIGMAK, SIGMAL and SIGMAPAR routines that take into account the finite collection angle but neglect any corrections due to the angular spread of the incident beam that may play a role as soon as $\alpha > \beta$ (Egerton, 2011b) or due to multiple scattering.

$$x_j = \frac{I_j(\beta, \Delta)}{\sigma_j(\beta, \Delta) * L_j * \tau} \times \text{constant} \quad (6a)$$

where

$$\sum_j x_j = 1 \quad (6b)$$

In the sense that the index j runs over all elements detected, this performs what is usually called a relative compositional quantification in at% (rather than an absolute quantification in terms of atomic areal density). As the scattering cross-sections in equation (6a) are for single scattering, while plural scattering is known to affect the edge shape, moving intensity from the onset towards higher energies, a reliable quantification would require either deconvoluting each spectrum in the SI to recover the single inelastic scattering contribution or integrating all net edge intensities over similar energy ranges so that all edges would be affected by multiple (plasmon) scattering to the same degree (Walther et al., 1995). Large integration windows can be used for edges at high energy losses that typically lie far apart from each other (here: Ga L and As L), while small integration windows must be used at lower energies (here: Si L and P L). Small integration ranges, Δ , tend to underestimate intensity considerably if thicknesses are large and the spectra are not deconvolved for multiple inelastic scattering. This has indeed been observed here, as deconvolution was not applied (see below). The algorithm generates maps which provide the spatial distributions of the elements in the material. The maps are generated by integration of background subtracted spectra at each point according to equation (6a). The background subtraction may not work perfectly for some spectra due to high noise or near edge structures which would contribute to inferior curve-fitting. Also, the EELS SI with 80eV offset revealed an artifact at around channel #100 due to the previous exposure of this area of the CCD to the zero-loss peak. This is shown in Figure 8. Hence, the map of the Al L-edge can only be evaluated with caution.

Insert Figure 8 about here

Some elemental maps in Figure 9 are very noisy, but the overall spatial distribution of elements can be clearly evaluated. While the map of the Al L_3 -edge is affected by the artifact as described above and can only be evaluated in so far as to rule out significant Al enrichment in any of the thicker regions, the Al K-edge at 1560eV is rather noisy but yields an Al K-map in Figure 9(c) that indicates that some Al may be present in parts of interfacial regions 4 and 6. The Al L_1 -edge is very weak and for quantification the corresponding map in Figure 9(a) cannot be directly used. For computation of the Al fraction in Table 2 we tentatively applied a partial scattering cross-section to Al L_1 one order of magnitude smaller than for Al L_3 , which will be an upper estimate as this transition is dipole-forbidden. The weak intensity in the Ge L-map is completely due to noise.

The quantification of individual spectra generally lacks statistics due to noise. Considering instead the sum of spectra from sub-regions as labelled in Figure 7(b) not only provides better SNR but a computationally viable method for quantification. Each inclined row marked by red lines in Figure 7(b) consists of 24 spectra (for EELS SI_1) or 47 spectra (for all other SIs), while the wider regions numbered 2, 3, 5 and 8 all contain several hundred spectra.

Screen shots of the program outputs are shown in Figures 9 and 10. It can be observed that the algorithm automatically detects the core losses and dynamically selects pre-edge regions and integration windows for each core-loss of the SI and that the output maps yield a quick visual feedback on the relative strengths of the chemical signals detected. Neglecting the signals from C (main surface contamination) and O (due to surface oxidation) the nominal values from Table 2 for wider regions 3, 5 and 8 would indicate chemical compositions of the underlying compound semiconductors of $\text{GaAs}_{0.84}\text{P}_{0.16}\text{:Si}$, $\text{Al}_{0.09}\text{In}_{0.37}\text{Ga}_{0.54}\text{P:As}$ and GaAs:P,Si respectively, where the elements listed after the colon refer to minority elements in the detection range of 1-2 at%, which however seems somewhat high for dopants. If we check the ratio of group III/ group V elements in these three compounds, i.e. $(x_{\text{Al}}+x_{\text{In}}+x_{\text{Ga}})/(x_{\text{P}}+x_{\text{As}})$, the values of 1.06, 1.04 and 0.91 obtained from the above three regions are in reasonably good agreement with the expected value of unity for a stoichiometric III/V compound semiconductor. As previously stated, the proposed method is mainly a demonstration of automated background subtraction by identifying core-losses, and plural scattering is not presently taken into account in Table 2. The effect from plural scattering could be pronounced for Al, Si and P $L_{2,3}$ -edges as these display slightly delayed onsets while the integration ranges are small. Hence the effect of plural scattering will move intensity from the edge onsets to values beyond the range of the actual EELS measurement (for P) or the integration range (for Al and Si), so the intensities in the experiment may be significantly lower than the cross-sections calculated for single scattering predict. A quick estimate based on the small widths of the integration ranges used here (15 eV for Al and Si, and 37.4eV for P) relative to the plasmon energy of GaAs (~16eV) shows that plural scattering could reduce intensities of the Al and Si L edges by factors of up to 2 for $t/\lambda \approx 1$, however, the concentrations for Al and Si are rather low anyway and so the precise values are perhaps not so relevant, while the effect on the P $L_{2,3}$ edge will be much weaker. The effect of plural scattering could in principle be minimised by deconvolution with the low loss spectrum, which we will explore in the future. The identification of the chemical composition in the smaller regions is strongly limited by counting statistics as well as a potential undersampling of the thinnest layers given the pixel sizes reported in Table 1. The implementation of the algorithm in Matlab R2015b means the code can be distributed not only to multiple processing cores (presently a PC with 2 cores is used) but to multiple computers using the Matlab parallel computing tool box.

Insert Figure 9 about here

Insert Figure 10 about here

		80eV offset			250eV offset			950eV offset		
	t/λ	Si L ₃	Al L ₁	P L ₃	C K	In M _{4,5}	O K	Cu L ₃	Ga L ₃	As L ₃
dispersion (eV/channel)		0.10	0.10	0.10	0.50	0.50	0.50	1.00	1.00	1.00
τ (sec)		0.50	0.50	0.50	0.50	0.50	0.50	2.00	2.00	2.00
Δ (eV)		15	15	37.4	50	89	50	200	200	200
region 1	0.52	1.44	3.22	5.47	44.09	2.37	43.40	0.00	0.00	0.00
region 2	0.96	1.51	2.08	3.89	30.03	0.00	38.30	24.18	0.00	0.00
region 3	0.95	7.87	0.00	6.26	9.29	0.00	2.41	0.00	41.46	32.72
region 4	0.95	8.53	1.63	40.73	18.61	10.37	0.00	0.00	10.07	10.05
region 5	1.01	0.00	3.99	43.48	10.10	16.90	0.00	0.00	25.02	0.50
region 6	1.04	3.82	1.62	29.97	4.84	3.61	0.00	0.00	22.80	33.35
region 7	1.04	1.57	3.17	49.16	7.87	19.08	0.00	0.00	8.92	10.23
region 8	1.11	8.07	0.00	1.92	0.00	0.00	1.50	0.00	42.94	45.57

Table 2. Quantification in at% of each region of the four Sis recorded. The sum of all concentrations has been normalised to 100% according to equation (6b).

Conclusion

The algorithm is robust in detecting ionization edges. Mapping of the core loss intensity is provided for quantitative assessment of sub-regions. Quantification can be done from spectra integrated over each sub-region. The ionization edges at low energies or edges which are very close to each other are always difficult to quantify as the background is difficult to subtract. Inconsistencies in gain correction of the detector are not taken into account in edge detection and background subtraction. Hence, a false positive identification of edges is possible at around channel #100 or more generally in the presence of excessive noise. The elemental maps produced by the proposed algorithm are in qualitative agreement with results from Gatan Digital Micrograph. The noise present in elemental maps can be reduced by applying image processing techniques. The effects from plural scattering have not been taken into account for quantification as yet but this needs to be done in the future and a graphical user interface is also in development.

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Figure captions

Figure 1: Comparison of noise suppression methods applied to an EEL spectrum. w describes the width (in pixels) of the filter mask. Principal Component Analysis (PCA) is not effective in suppressing shot noise as the reconstruction based on the sum of the first 17 components (shown at the top) still contains noise. The median filter works best.

Figure 2: Original spectrum of Si L-edge and C K-edge (in dark blue) and angle as defined in equation (3) (in red) showing the presence of clusters in the latter correlates with the onset of ionization edges.

Figure 3: Flow chart for edge detection in spectra that consist of 1024 channels. c =count of channels with positive gradient, i =energy channel, j =loop count, w = window width, mod = modulo operator (remainder after division).

Figure 4: The location of core-loss (here: Si L-edge) is detected from the look-up table and fine-tuned as per equation (4).

Figure 5: Histogram distribution of edge onsets detected for EELS SI from semiconductor heterostructure shown in Figure 7 for 80eV offset (a), 250eV offset (b) and 950eV offset (c). The edges are later identified in Table 2.

Figure 6: Block diagram of ionization core-loss edge selection and background subtraction.

Figure 7: (a) An annular dark-field (ADF) image showing an overview of the layer structure analysed and indicating the rectangular regions selected for spatial drift (yellow) and spectrum image acquisition (green). (b) Definition of regions in the EELS SI. A sum spectrum is extracted from each region for further quantification in Table 2.

Figure 8: The persistence of an artifact at 72 – 85eV in spectra from all locations (3 single spectra are displayed) shows that the Al L₃-edge (nominally starting at 73eV) cannot be evaluated from spectra acquired with 80eV offset after spectra without offset had been acquired.

Figure 9: Set of maps generated with EELS SI of 80eV offset (a), with 250eV offset (b) and with 950eV offset (c). The elemental maps show the spatial distribution of Al L₃, Si L₃, Al L₁, P L₃, C K, In M_{4,5}, O K, Cu L₃, Ga L₃, Ge L₃, As L₃ and Al K edges. Al L₃ is a false positive detection due to an artifact. Maximum intensity values in kilo-counts after background subtraction, integration and scaling according to equation (6a) with constant=1.

Figure 10: Screen shot of program output showing pre-edge regions and integration windows dynamically assigned by the algorithm for SI with 80eV offset (a), 250eV offset (b) and 950eV offset (c).

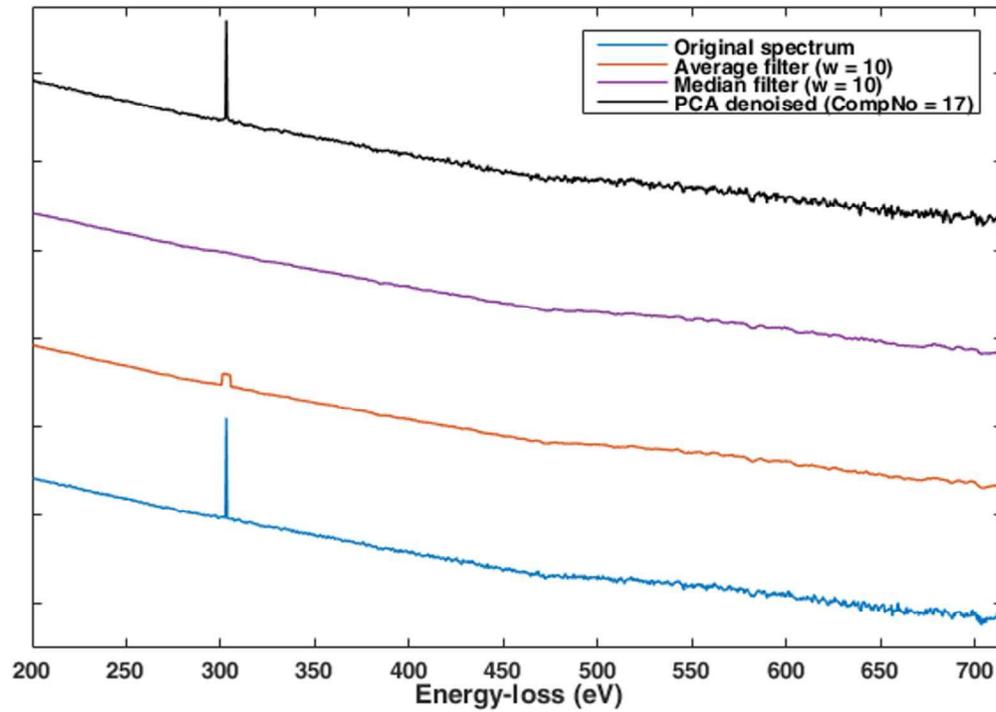


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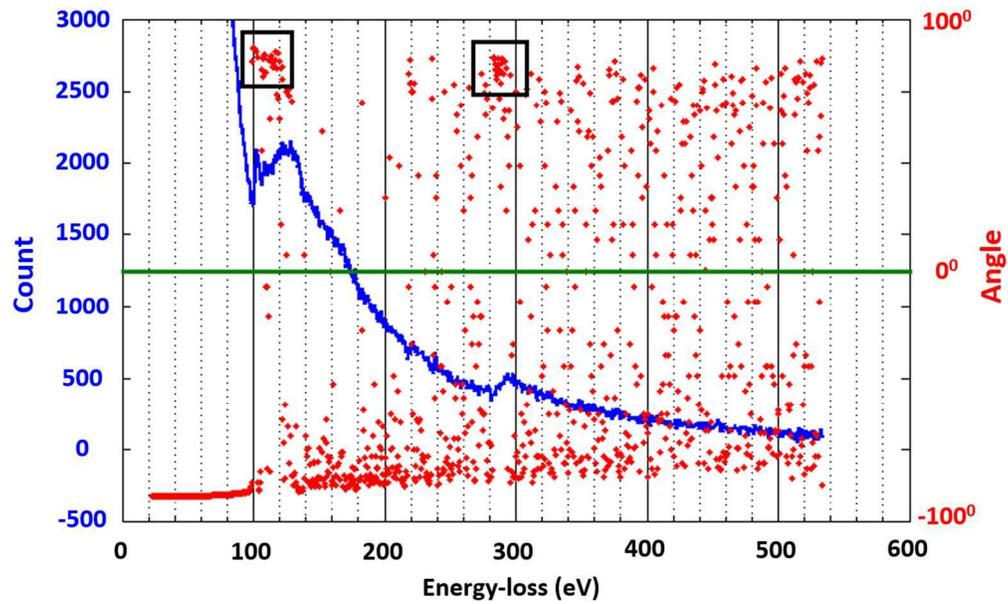


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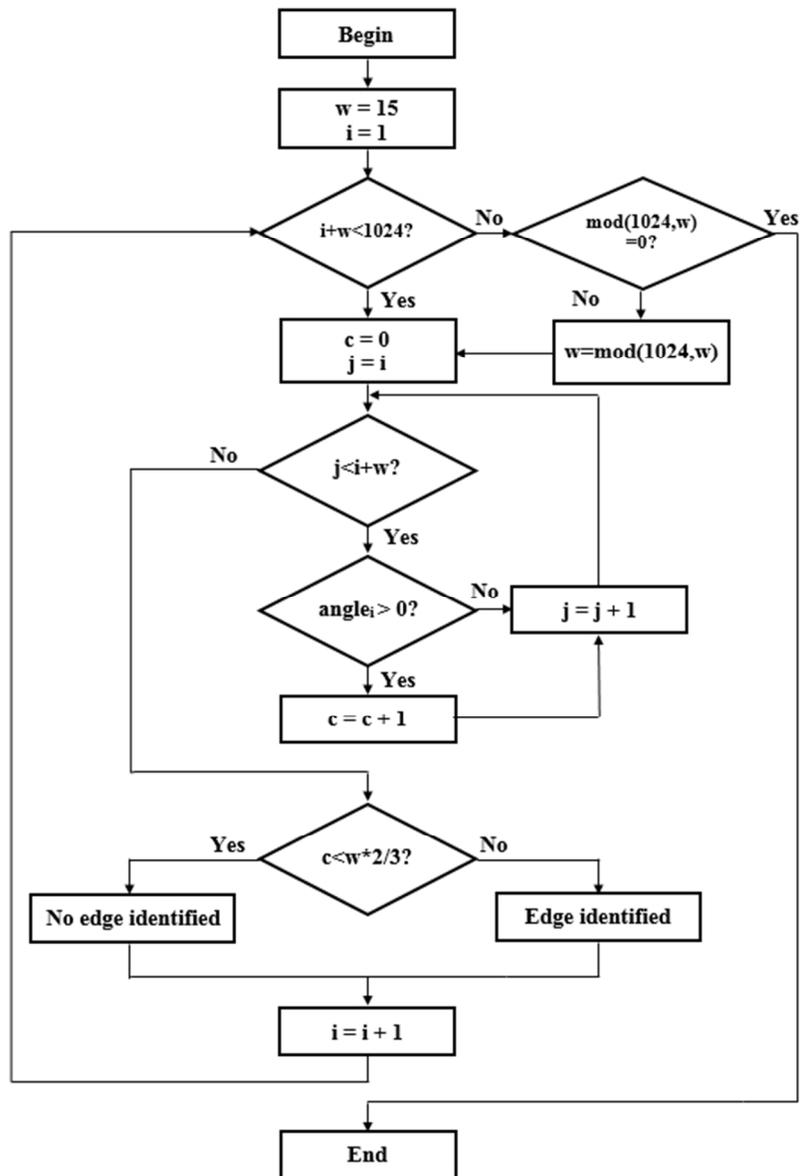


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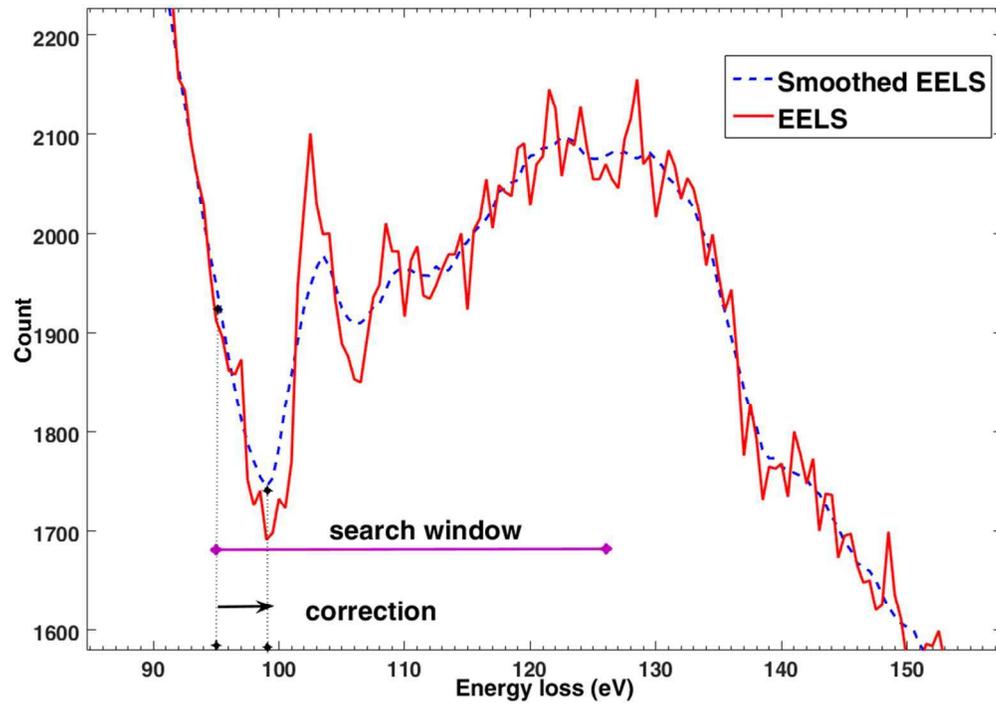


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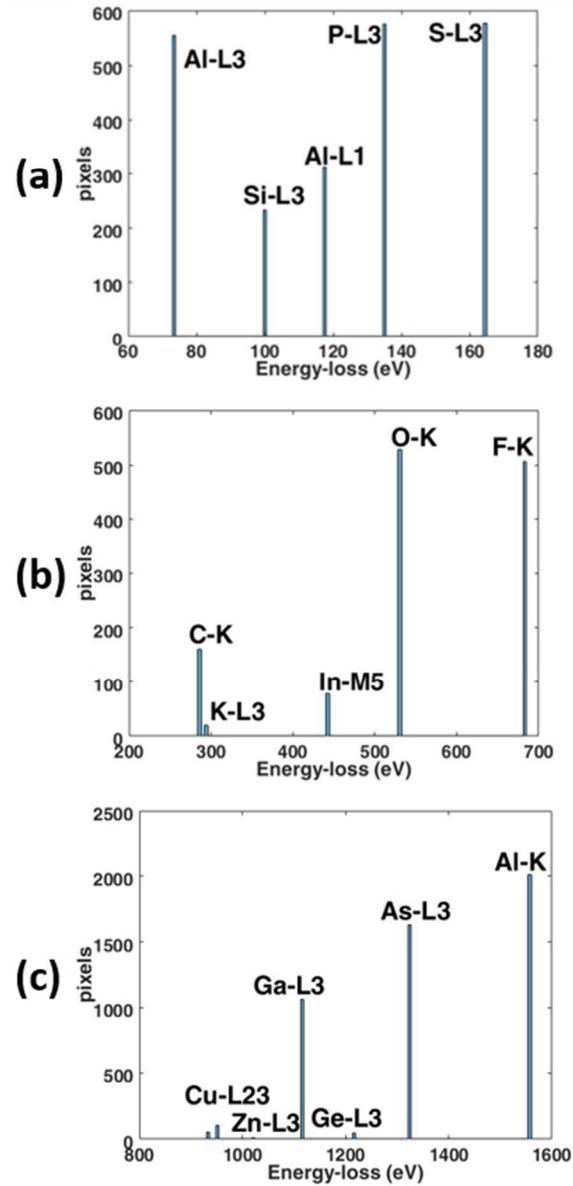


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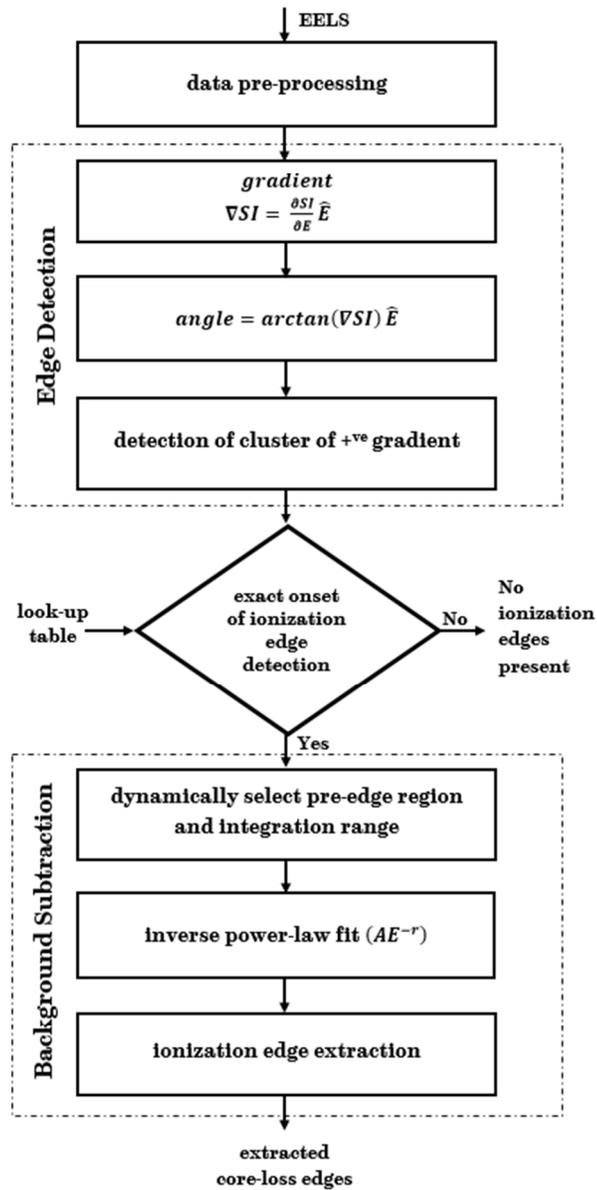


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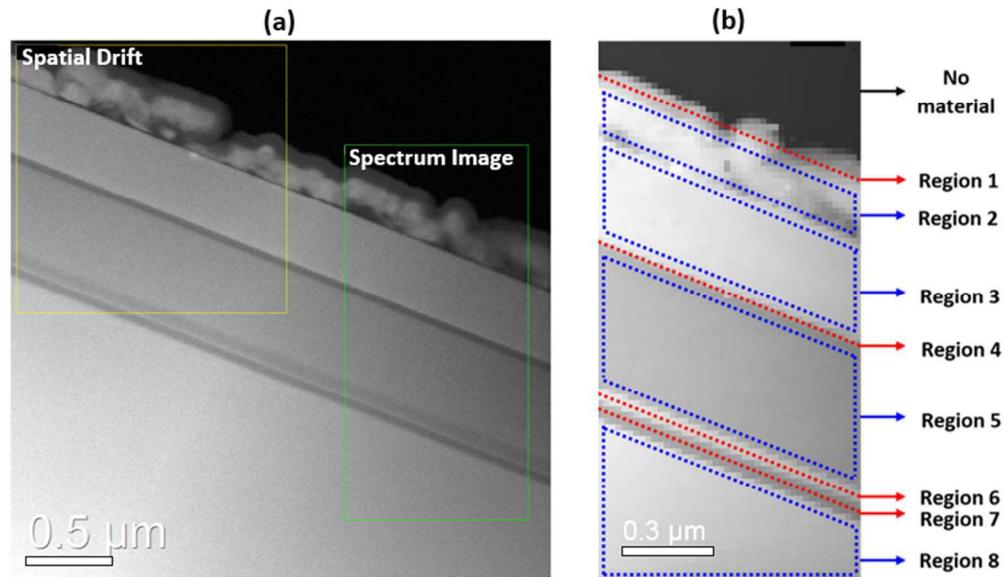


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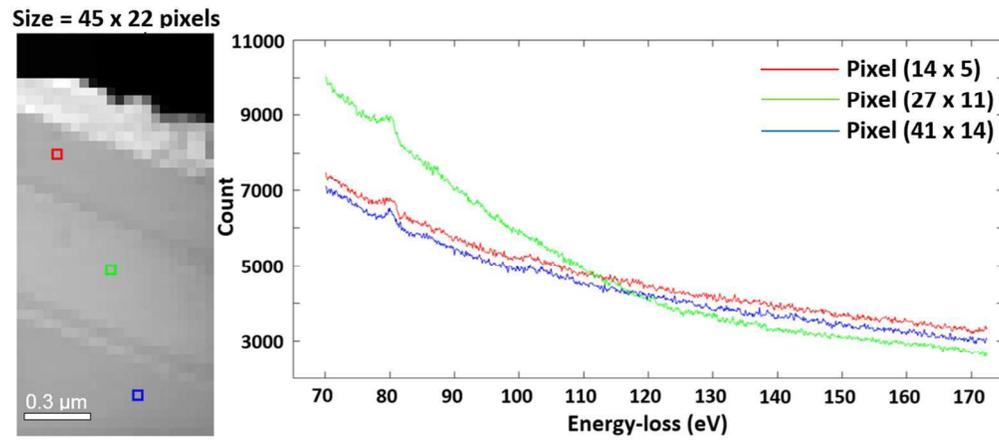


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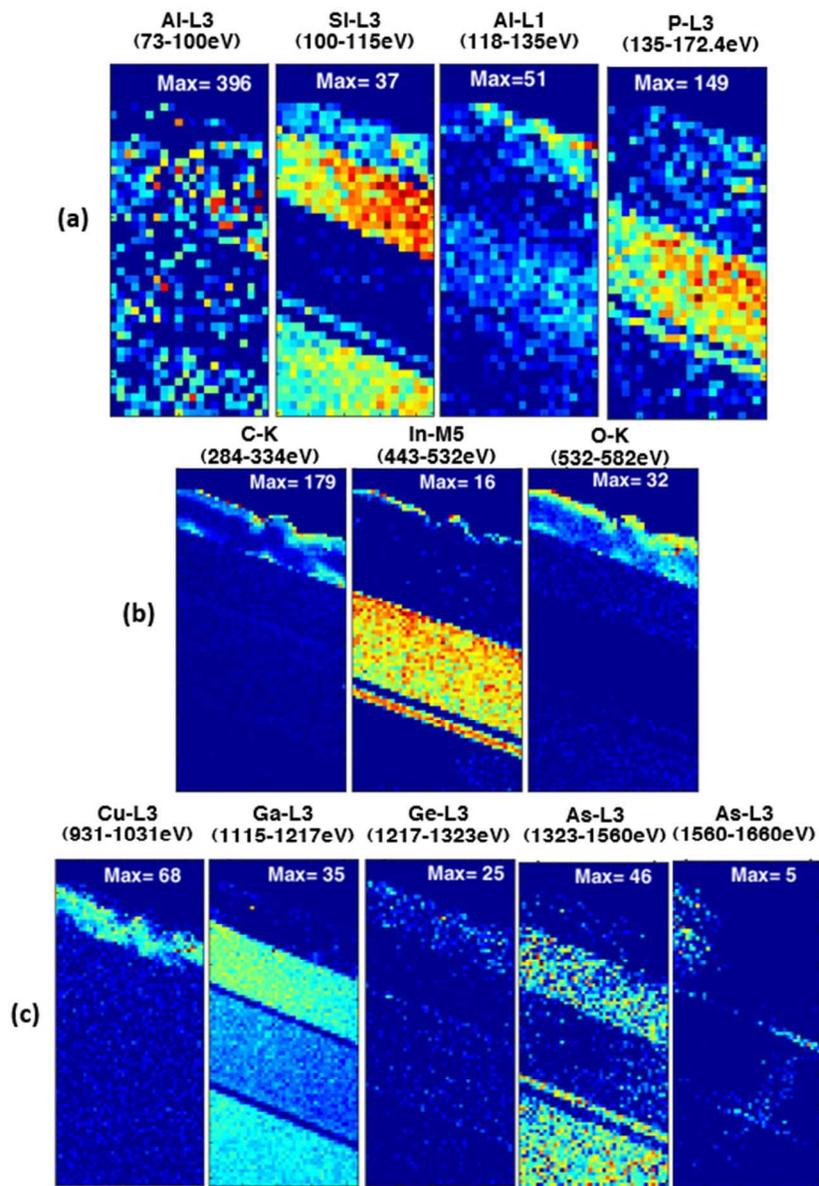


Figure 9: Set of maps generated with EELS SI of 80eV offset (a), with 250eV offset (b) and with 950eV offset (c). The elemental maps show the spatial distribution of Al L3, Si L3, Al L1, P L3, C K, In M4,5, O K, Cu L3, Ga L3, Ge L3, As L3 and Al K edges. Al L3 is a false positive detection due to an artifact. Maximum intensity values in kilo-counts after background subtraction, integration and scaling according to equation (6a) with constant=1.

Detected edges :					
73 100 118 135 165					
Delta for edge 165eV is exceeding energy-loss axis limit (172.4eV)					
Edge considered for quantification :					
73 100 118 135					
-----Pre-edge region-----					
	<u>Range eV</u>	<u>Begin eV</u>	<u>End eV</u>	<u>Onset eV</u>	
(a)	1	72	72.8	73	
	14	86	99.8	100	
	9	109	117.8	118	
	9	126	134.8	135	
-----Integration region-----					
	<u>Onset eV</u>	<u>Element</u>	<u>Begin eV</u>	<u>End eV</u>	<u>Integration Range eV</u>
	73	'Al-L3'	73	100	27
	100	'Si-L3'	100	115	15
	118	Al-L1'	118	135	15
	135	'P-L3'	135	172.4	37.4

Detected edges :					
284 294 443 532 685					
Delta is overlapping with next edge. Edge 294eV is omitted					
Delta for edge 685eV is exceeding energy-loss axis limit (712eV)					
Edge considered for quantification :					
284 443 532					
-----Pre-edge region-----					
	<u>Range eV</u>	<u>Begin eV</u>	<u>End eV</u>	<u>Onset eV</u>	
(b)	42	242	283	284	
	80	363	442	443	
	45	487	531	532	
-----Integration region-----					
	<u>Onset eV</u>	<u>Element</u>	<u>Begin eV</u>	<u>End eV</u>	<u>Integration Range eV</u>
	284	'C-K'	284	334	50
	443	'In-M5'	443	532	89
	532	O-K'	532	582	50

Detected edges :					
931 951 1020 1115 1217 1323 1560					
Delta is overlapping with next edge. Edge 951eV is omitted					
Delta is overlapping with next edge. Edge 1020eV is omitted					
Edge considered for quantification :					
931 1115 1217 1323 1560					
-----Pre-edge region-----					
	<u>Range eV</u>	<u>Begin eV</u>	<u>End eV</u>	<u>Onset eV</u>	
(c)	40	891	929	931	
	92	1023	1113	1115	
	51	1166	1215	1217	
	53	1270	1321	1323	
	119	1441	1558	1560	
-----Integration region-----					
	<u>Onset eV</u>	<u>Element</u>	<u>Begin eV</u>	<u>End eV</u>	<u>Integration Range eV</u>
	931	'Cu-L3'	931	1031	100
	1115	'Ga-L3'	1115	1217	102
	1217	'Ge-L3'	1217	1323	106
	1323	'As-L1'	1323	1560	237
	1560	'Al-K'	1560	1660	100

Figure 10: Screen shot of program output showing pre-edge regions and integration windows dynamically assigned by the algorithm for SI with 80eV offset (a), 250eV offset (b) and 950eV offset (c).

Lay Summary

Electron energy loss spectroscopy (EELS) has become a standard tool for identification and sometimes also quantification of elements in materials science. This is important for understanding the chemical and/or structural composition of processed materials. In EELS, the background is often intense and can be modelled over small energy ranges using an inverse power-law function. On top of this background, core-loss edges are superimposed that are due to the ionization energies characteristic of each element. This study describes a Matlab algorithm to automatically detect and quantify core-loss edges based on a single inelastic scattering approach, without any prior knowledge of the material. The algorithm provides elemental maps and concentration profiles by making smart decisions in selecting pre-edge regions and integration ranges. Deconvolution to take into account plural scattering is not considered yet but will be integrated in a future version.