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Deep Learning-based Blind Denoising for Enhancing Energy-dispersive X-ray Spectroscopy (EDS) Images

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It is now possible to form high-resolution energy dispersive X-ray spectrometry (EDS) maps using both SEM/(S)TEM instruments. However, a major drawback of EDS is the requirement of a long dwell time to acquire enough counts to form a clear image, which is often not possible when imaging beam sensitive materials [1] requiring a shorter dwell time to minimize beam damage. Operating the instrument to account for the damage tolerance of the sample results in EDS maps with poor signal-to-noise ratio.

Recently powerful methods for denoising have emerged from the deep learning community. Supervised methods [2] make use of a 'ground truth' to train a deep neural network (DNN), capable of denoising images, by mapping the noisy image to a clean reference. This can achieve state-of-the-art performance with a large enough data set but can struggle to adapt to unseen data with new models of noise. For the EDS case, a 'ground truth' image may not be possible to acquire without damaging beam-sensitive materials. It is possible for a DNN to instead learn the mapping between independently measured noisy images to predict a clean signal with no reference ground truth [3], achieving competitive performance with the supervised approach. *Noise2Self* [4] recently extended this idea to exploit the noise independence between pixels, relaxing the requirement for collecting two independent noisy images and providing theoretical performance guarantees of such an approach.

This work extends the *Noise2Self* innovations to hyperspectral (HSI) EDS images. A 3D *convolutional autoencoder* is trained to reconstruct the noisy HSI image from a Bernoulli sampled version. The use of a 3D *convolutional neural network* extends the *local receptive field* of the network, considering the volume of pixels over the spectra in the denoising process, rather than just the neighborhood pixels of the individual 2D images. Through training, the DNN can 'learn' the correlation between the spectral bands, considering the feature relationships over the full spectra. The exploitation of this spectral redundancy of features allows the network to correctly inpaint the masked pixels from the Bernoulli sampled input by considering the spatial, and spectral context of the masked pixels. Once trained, the original weakly sampled image can be denoised by using the full noisy HSI image as the input to the network. This same model has been improved by expanding the spectral input with the high-resolution Z-contrast image, enabling a pansharpening effect, fusing the high-resolution spatial information of the contrast image with the EDS maps to further enhance the image.

In this presentation, we will discuss the applicability of the proposed model for the case of denoising and enhancing hyperspectral microscopy images obtained with a low dose.

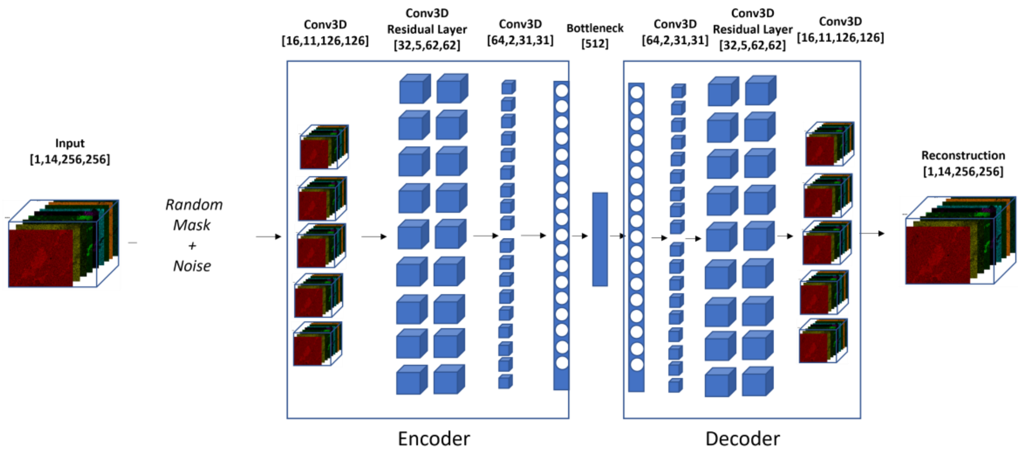

Figure 1. High-level overview of the proposed DNN structure. The encoder applies successive 3D convolution operations to the masked HSI input, an intermediary residual layer before compressing the information to a *bottleneck.* The decoder then upsamples the image back to the full spectral cube using the 3D transposed convolution operation.

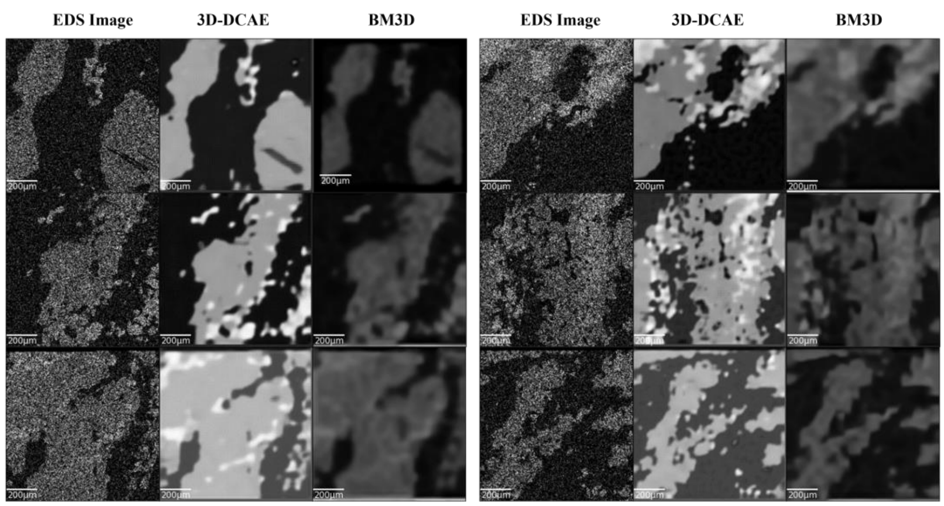

Figure 2. Clear examples are shown of the pansharpening effect in the reconstructions when using the proposed DNN (labelled 3D-DCAE – 3D denoising convolutional autoencoder) with the contrast image. These reconstructions retain more complex signal patterns, improve the contrast in the image when compared to the traditional BM3D method and can greatly improve the reconstruction quality in poorly sampled bands.

References:

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