An adaptive neural network for the restoration of SEM pictures

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Spatial resolution is the very reason for the existence of microscopes. The laws of physics state that any optical (or electron-optical) system is ultimately limited by diffraction. In practice other factors concur to reduce the practical resolution of electron microscopes. All the sources of image degradation converge into the so-called point spread function (PSF) of the optical system, which introduces an unwanted blur in the final image.

If the PSF can be measured of modeled, then it is possible to subtract its effect from the final image. This is usually done in the Fourier space by a Wiener deconvolution that can be a fast and extremely effective process. This approach is unfortunately impractical for the SEM, where the image is formed not by the primary electron beam but by secondary electrons emerging from the specimen surface after a random anelastic scattering. Even if a hypothetical, perfect lens were able to force the entire electron beam along a single line, the secondary electrons would still arise from a finite area, its extent depending from the local geometry and composition of the specimen. A maximum likelihood [1] or constrained least square error [2] approach is therefore better suited to regain some sharpness in this case.

The image degradation model used for most practical purposes is a linear process with additive noise of the form $\mathbf{g} = \mathbf{Hf} + \mathbf{n}$, where $\mathbf{g}$ and $\mathbf{f}$ are the degraded and original images respectively, $\mathbf{H}$ is the degradation matrix, and $\mathbf{n}$ represents the noise. Generally speaking, the aim of any image restoration process is to find an estimate that closely approximates the original image $\mathbf{f}$, given $\mathbf{g}$. In the presence of random noise, which in SEM images is usually far from negligible, the restoration process requires the specification of additional smoothness constraints on the solution. This is usually accomplished in the form of a regularization term in the associated cost function. Regularized image restoration methods aim to minimize the constrained least-squares error measure $\mathbf{E} = \frac{1}{2}||\mathbf{g} - \mathbf{Hf}||^2 + \frac{1}{2}\lambda||\mathbf{Df}||^2$, where $\mathbf{f}$ is the restored image estimate, λ represents the regularization parameter and $\mathbf{D}$ is the regularization matrix. A small λ, which deemphasizes the regularization term, implies a better feature extraction but less noise suppression in the restored image, whereas a large value leads to better noise suppression but also to more blurred features.

Since different parts of the same figure often show different degrees of blur, it is important that the regularization term can be adjusted dynamically so as to provide the best balancing for any given situation. In addition of adapting itself to the local features of the image, this auto-tuning has the advantage of making the restoration process as independent as possible from the operator input, opening the way to a blind restoration. This is an important feature, since it is desirable to eliminate as much as possible of the human guesswork.

In the present implementation of the algorithm, a neural network is created with a neuron for each pixel of the original image. The pixels of the restored image can be viewed as the synaptic weights that the neural network adjusts during its unsupervised learning to minimize the output error measure. The value of λ is computed for each pixel depending from a parameter proportional to the local sharpness, which currently is the gradient of an isotropic Bessel filter.

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It must be noted that, because of the sampling inherent to digital imaging, not all images are suited to the restoration process. The Nyquist-Shannon theorem states that a hypothetical resolution **R** can be fully exploited only if the pixel-to-pixel spacing is smaller than **½R**. An estimated (and rather conservative) resolution of 6 nm implies a pixel spacing not greater than 3 nm, a value that with our SEM and our 1424x968-pixel framestore is reached at approx. 30,000x. At lower magnifications the resolution is limited by undersampling rather than by diffraction, while at much higher magnifications the image becomes unnecessarily oversampled. Under our working conditions, image restoration only makes sense within an approximate range of 30,000x to 60,000x.

In its present form the program takes a couple of minutes to process a whole 1424x968-pixel image on a typical PC and, in terms of improvement in the signal-to-noise ratio measure (ISNR), on test images it already outclasses the reference Hopfield neural model [3]. Although the software is already in use in our laboratory, in its present state it is best seen as a development platform. Further research is in progress to evaluate other local properties which may better characterize the local blur and the local S/N ratio.

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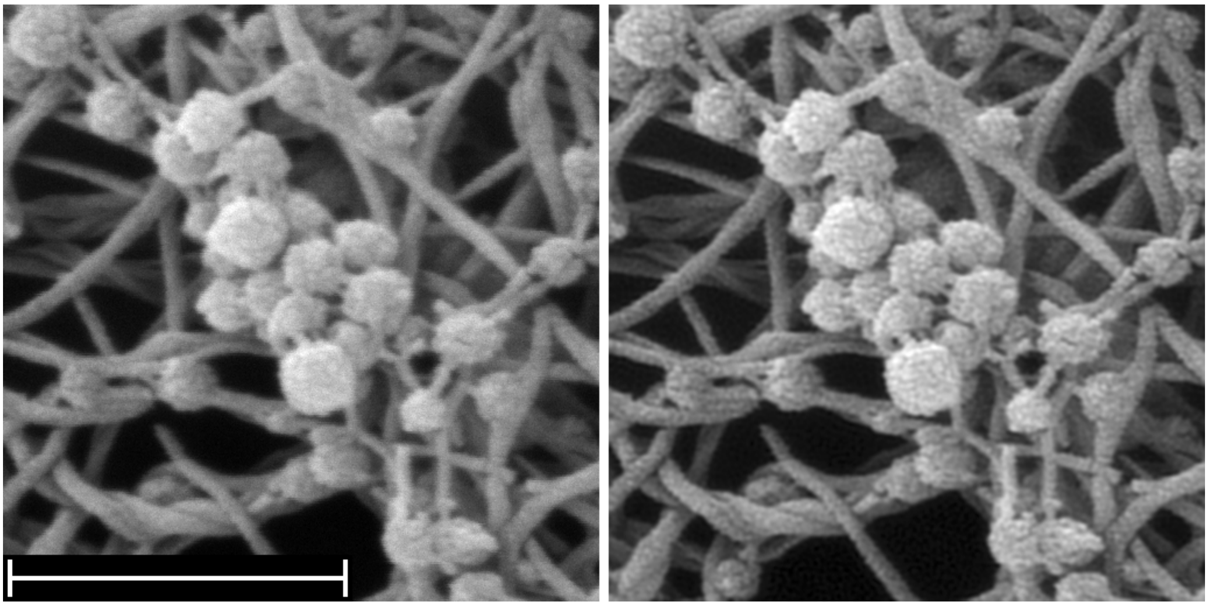

Figure 1. SEM micrograph of a macromolecular complex in the extracellular matrix. On the left, a detail of the unretouched picture (bar=500nm, original magnification 50,000x); on the right, the same picture after unsupervised processing.

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