Reconstruction of Electron Holograms in Real Space with a Neural Net

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Off-Axis-Electron-Holography [1] uses a Möllenstedt biprism [2] to interfere the image wave with the reference wave. The fringes of the interference pattern at the position contain the information about amplitude A and phase Φ of the complex electron image wave,

$$= \; + \; + \; \cdot \; p \; + \Phi \;,$$

with contrast V and space frequency of the fringes.
The classic reconstruction scheme for off-axis electron holograms uses the linear reconstruction technique by means of Fourier transformation of the hologram, cutting out the sideband representing the image wave $^{\Phi}$, and an inverse Fourier transform; this is in analogy to an optical bench where the sideband is cut out in the focal plane. Today, this process, implemented as computer software, is still in use because it yields optimum results as long as there is no noise, no difference in the detection efficency of the CCD pixels, and the number of CCD pixels is unlimited. Real electron holograms, however, suffer from all these restrictions. One fast way to eliminate these effects is the use of an artificial neural network, because neural nets can learn nonlinear functions of many input variables and can thus use both nonlinear and linear part of .

Artificial neural networks attempt to simulate the flexibility of biological networks on a computer. We used a feed-foreward network, which converts the information from training patterns to matrix elements in the weight matrices $\mathbf{W}$ of the network. The output y of a neuron k is given by

$$= \sum_{=} \;,$$

where S is a sigmoid function like the $tanh$ function, and n is the number of input neurons. A complete neural net is a combination of two or more neuron layers. The learning process starts with completely arbitrary matrices and continues until the user is satisfied with the result. One critical point in the application of neural networks is the appropriate generation of training patterns. These patterns should contain a variety of good, representative experimental examples, although they can not cover all the imaginable cases.

In our experiment, the complex image is reconstructed in real space. Since the correlation between the values of two different pixels in the image wave vanishes quickly with their mutual distance, it is sufficient to use a small area of hologram pixels to calculate the image wave in the center of this area. We usually use a 7 x 7 area and thus have a vector $=$ of intensities as input information for the neural net.
The neural net of the feed-foreward type (fig. 2) was simulated with the Stuttgart Neural Net Simulator (SNNS) [3] on a Power PC. During training, we use input

intensities resulting from well known simulated holograms, including all the disturbances mentioned above. After training the net, the weight-table was translated to fast C code. Using this program, we were able to reconstruct simulated and real holograms with speeds comparable to the conventional reconstruction process but with a better performance in noise reduction and artefact elimination.

A first result is shown in figure 3. The electron hologram of a Si specimen (fig.1) was used as input to the neural net shown in figure 2. The net is build up by 49 input neurons, 10 neurons in the first hidden layer, 5 neurons in the second hidden layer and two output neurons, which represent real and imaginary part of the image wave; the layers are completely connected, i.e. the matrices $\mathbf{W}$ have no zero elements.

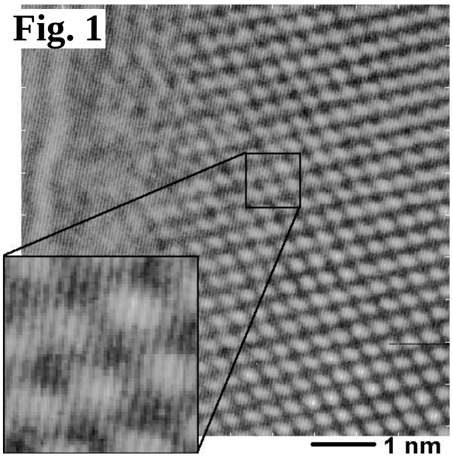


Fig.1: Electron hologram of Si in (110) orientation. The image was taken on the CM30 in Tübingen, using a 1k CCD camera. In the inset the holographic fringes are clearly visible

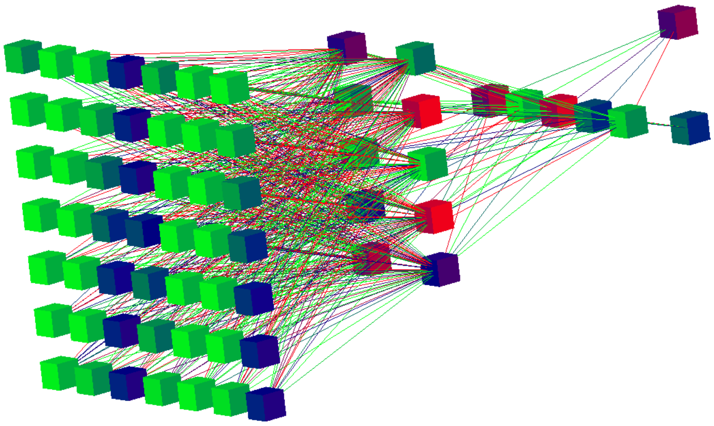
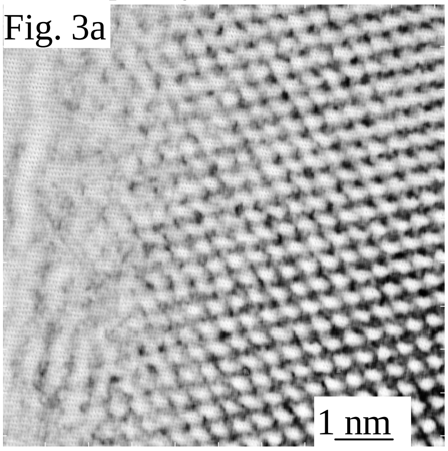


Fig.2: Neural net for the reconstruction process. The input layer shows the applied fringe pattern.



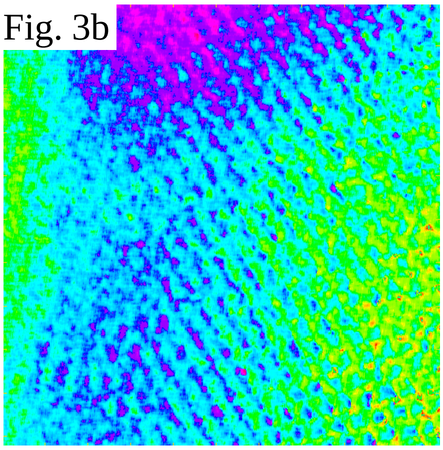


Fig.3a: Amplitude of the electron wave, reconstructed by the neural net shown in figure 2 using the hologram (fig. 1) as input. b: Phase of the same area.

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