Image restoration from single scanning transmission electron micrograph using deep convolutional neural networks

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Experimental STEM images show a combination of distortions, which depend on the instrument, environment, scanning instabilities, scan-speed and electron dose [1-2]. Such distortions hamper the extraction of quantitative structure information. Fast acquisitions at low dose are often preferred in order to minimize drift, beam damage, charging, and specimen rotation. However, this results in frequency distortions in the kHz-MHz regime, which are unfortunately very strong and often strongly correlated along the fast-scan direction. Such distortions even persist when using several frames with the existing state-of-the-art non-rigid registration [3] and therefore novel methods are needed to overcome this problem.

To compensate for scanning distortions, we apply the concept of machine learning using a deep artificial neural network. This approach has become state-of-the-art because of its ability to learn from data by adjusting the weight connections between neurons in the network during its training process. In particular, convolutional neural networks (CNNs) have resulted in a breakthrough for various tasks [4 - 6]. The restoration procedure we propose here is based on the use of a deep convolutional neural network that directly learns how to map between distorted and undistorted STEM images. By training the neural network, it implicitly learns to detect the presence of distortions and to correct for them, regardless the level and combination of distortions present in the image that is used as an input. The architecture that we propose for the network consists of a stack of 12 layers, where each layer is composed of a linear convolution followed by an elementwise Rectified Linear Unit. All layers consist of 64 filters (except for the last one which consists of a single filter) and have a spatial filter size of 5x5. Using the Caffe framework [7], the unknown parameters are determined by minimizing the standard mean squared error employing the Adam learning algorithm followed by the SGD learning algorithm. This combination has been shown to have optimal convergence results [8]. Since we are experimentally hampered by the fact that we can only collect distorted images, a set of undistorted and distorted images has been simulated to create our training dataset. After training, this network can be used to correct all distortions from single-shot STEM micrographs.

The reliability of our trained deep CNNs is shown in figure 1 for a variety of experimental images of arbitrary samples. The restored images demonstrate impressive results independent of the level and combination of distortions, validating our training procedure as well as our models used for synthetic data generation.

References

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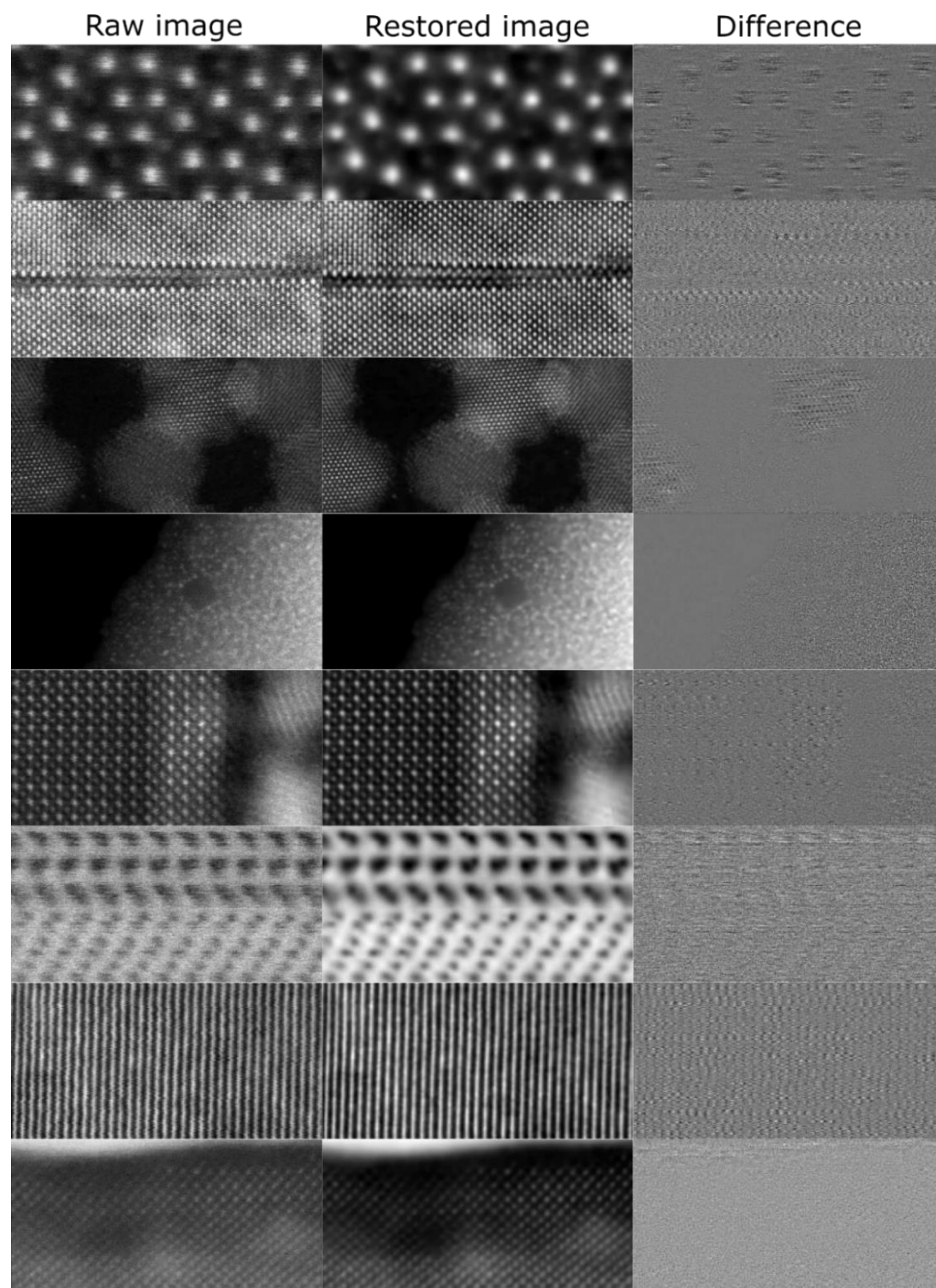

Fig. 1. Experimental STEM micrographs containing different levels of distortions. Raw image, restored image and difference is shown in the first, second and third column, respectively.