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Meeting-report

Real-time Image Deblurring to Improve Throughput of Serial-Section Volume Electron Microscopy for Neural Connectomic Studies

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Generating large serial-section electron microscopy volumes requires automated and reliable image acquisition. In particular, image quality reliability is of paramount importance as retaking out-of-focus, or soft-focused images dramatically decreases the overall imaging throughput. As an example, when collecting a 1.3 PB data set consisting of ~5000 serial sections, acquiring images from one section took ~30 min and consisted of 45,750 images (~230 million total images) [1]. Retaking 2% of these images requires breaking the automation and human intervention at least once per day. Since most low-quality images exhibit soft focus, post image correction with machine learning, may be an alternative to image re-acquisition. Out-of-focus, or blurred images arise for several reasons: a problem with the focusing algorithm, a problem with the stigmation algorithm, surface defects, or non-flat fields-of-view. Removal of image re-acquisition efforts not only improves large serial EM dataset throughput, but also improves the overall image acquisition performance of smaller datasets where labor costs, storage costs, and machine rental costs are major project considerations. To increase the throughput imaging rate of serial section EM, we have developed a machine learning-based, real-time image deblurring tool that eliminates the need for retaking out-of-focus images.

We use a method proposed by Zhang *et al.* [2] to deblur out-of-focus images. This method is based on a graph reasoning attention network (GRAN) and not on more traditional deep convolutional neural deblurring networks. The method initially performs feature downscaling before feeding the features to a graph reasoning attention block (GRAB) and then performs upscaling, resulting in efficient computation and a larger receptive region. We model the extracted feature points as visual components and construct a fully connected relationship graph. Next, a graph convolutional network (GCN) analyses the relationship graph. The GCN combined with the residual learning gives us our GRAB blocks. The features obtained from GRAB can be treated as attention, then upscaled and used to generate the corrected image. The model is trained by computing the pixel-wise L1 loss and an adversarial loss between the ground truth image and the corrected image.

The SEM images presented in Figure 1 compares out-of-focus image with the ML corrected image, and a properly focused image. The data indicate that for most out-of-focus images the corrected images are very similar to the ground truth images. The change in PNSR indicates a significant improvement of the corrected images compared to the out-of-focus images. As expected, severely out-of-focus images cannot be properly corrected. The limits of effectiveness of the deblurring algorithm is currently being tested.

Implementation of the deblurring algorithm will be instantiated by including the correction algorithm in the image acquisition pipeline. Here the image quality is determined using an in-house algorithm [3]. If the image quality is below a predetermined threshold, the out-of-focus image will be corrected using the deblurring algorithm. [4]

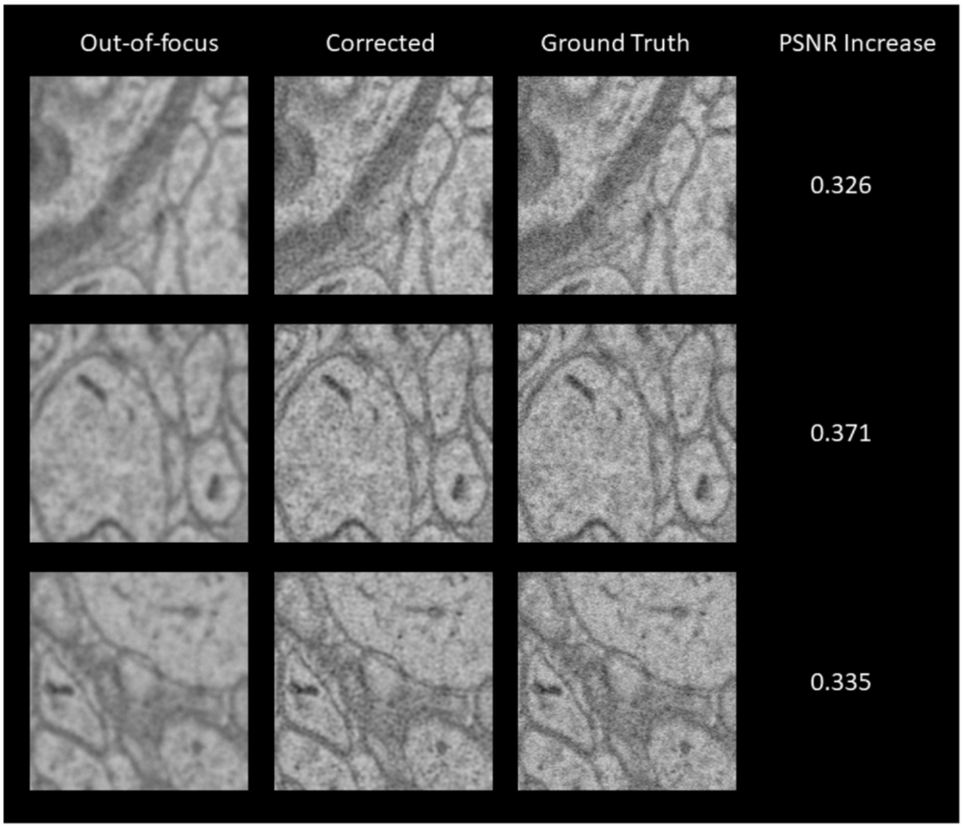

Fig. 1. Comparison of the out-of-focus, corrected and ground truth images.

References

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