NEURAL NETWORKS FOR PROCESSING EM IMAGES

Pavel Potocek

Thermo Fisher Scientific, Eindhoven

Abstract

Neural networks provide relatively new tooling for the image processing. There is a broad range of applications in the processing of images from an electron microscope (EM) where they can be applied. This contribution selects a few examples of possible usage of especially convolutional neural networks (CNN). It is shown that they can produce results which are superior to the classical algorithms. The demonstration is mostly based on examples from life science.

The (scanning) electron microscopy (SEM) plays an important role for many life science projects. The understanding of brain connectivity is receiving a lot of attention. The fast or time optimal acquisition of large volume data and understanding it are the key factors in such a process [1]. This presentation shows some of the possible key contributions we already see from techniques related to the neural networks.

1 Super-resolution techniques

Super-resolution algorithms provide a higher resolution image output while there is only a smaller resolution input image. This brings the possibility to acquire a SEM image with a low resolution and thus spend only a fraction of the time needed to acquire a higher resolution image. There are many examples of neural network based methods [2]. The basis for the majority is a very deep super-resolution net (VDSR) and deep residual nets (ResNet). All of them perform better compared to the ‚standard' bicubic up-scaling and with a PSNR of around 35dB they can provide very high quality reconstructions.

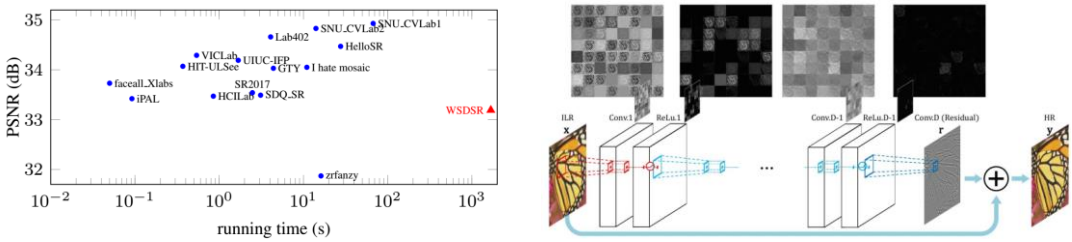

Figure 1: Reconstruction quality comparison for several algorithms and structural diagram for the residual VDSR model based on VGG-16 architecture [2].

2 Compressive sensing reconstruction

Another way to increase the SEM acquisition performance is compressive sensing (CS) [3,4,5,6]. CS is a technique for efficient acquisition and reconstruction of a signal. Using an optimization process, the signal can be recovered from less samples than required by the Shannon-Nyquest sampling theorem. The original CS reconstruction algorithms are computationally and time demanding. The latest experiments indicate that trained deep networks can closely approximate the solutions provided by state-of-the-art CS recovery algorithms. But they can be a couple of magnitude faster in run time.

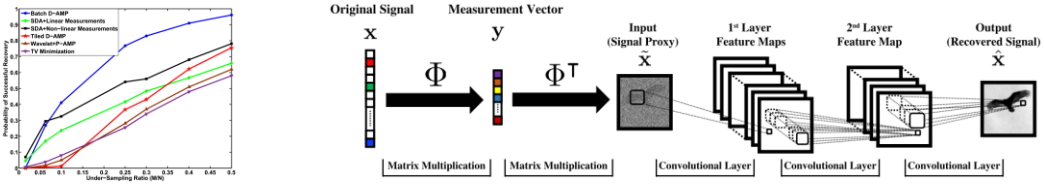

Figure 2: Signal recovery probability for different algorithms and different under-sampling ratios [6].

3 Image Segmentation

Image segmentation is one of the most important tasks in life science image analysis. segmentation aims to divide the image into a patchwork of regions, each of which is 'homogenous' in some sense – representing different structures. Accurate reconstruction of anatomical connections between neurons in the brain using electron microscopy (EM) images is one of the most important techniques for circuit mapping and understanding neuron functions. A key step in obtaining the reconstruction is the ability to automatically segment neurons with a precision close to human-level performance. Recently, the algorithms based on a modified U-Net architecture can even out-perform a human operator.

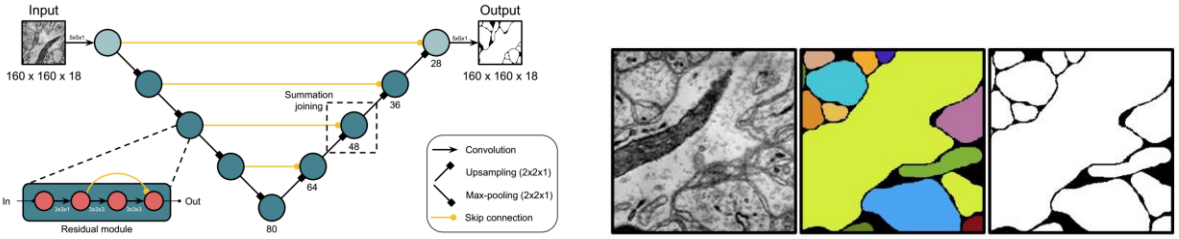

Figure 3: Residual Symmetric U-Net architecture. The images on the right side represent the input, the segmentation and the boundary map. [7]

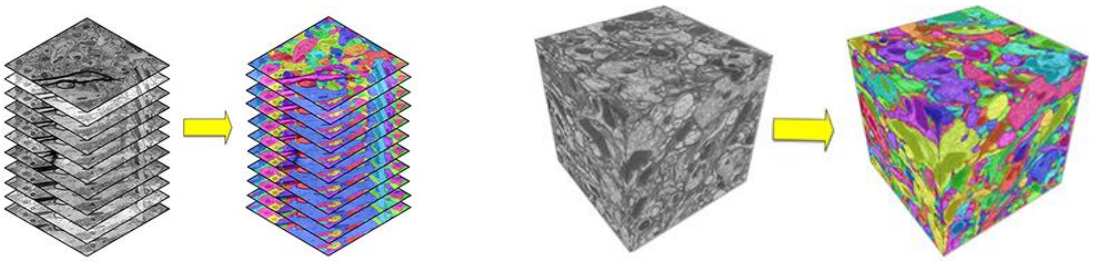

Figure 4: The results of color-coded segmentations of neurons from a small part of brain tissue and the input raw gray-level images from an electron microscope [8].

References

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Pavel Potocek
pavel.potocek@fei.com