Image restoration using deep convolutional neural networks applied to high-speed optical microscopy of living samples

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We report on ongoing work on methods that enable significant increases in the acquisition frame rates of optical microscopes through the application of deep learning for image restoration. Optical imaging of dynamic processes in living cells is a problem that necessitates the use of minimal illumination intensities while operating at high imaging speed. Low excitation powers must be used to reduce photodamage and avoid non-physiological behaviour in the sample. At the same time, the frame rate must be sufficiently high so that relevant movement can be captured, which in turn leads to signal reductions in the collected images. To satisfy the simultaneous requirement of low-intensity excitation and high frame rate, a trade-off must be made with image quality. Depending on the time scale of the dynamic process of interest, this sacrifice leads to poor signal-to-noise ratio that render quantitative analysis futile. In this work, we present methods to address this problem by leveraging recent advancements of deep Convolutional Neural Network (CNN) architectures, which offer completely new modalities for image restoration tasks such as denoising, super-resolution, artefact removal and deblurring [1-3]. Using datasets constructed by systematically reducing the exposure times, we train deep CNNs in a supervised manner to restore the degradation by mapping noisy images to denoised, clean versions. We test the trained models on an independent dataset acquired from another sample, and confirm that the denoising performance on the test set is acceptable, indicating that the models have generalised well under training. This ability to image samples at reduced signal-to-noise ratios may open the window to a large number of very dynamic biological processes, which have so far eluded microscopic imaging techniques.

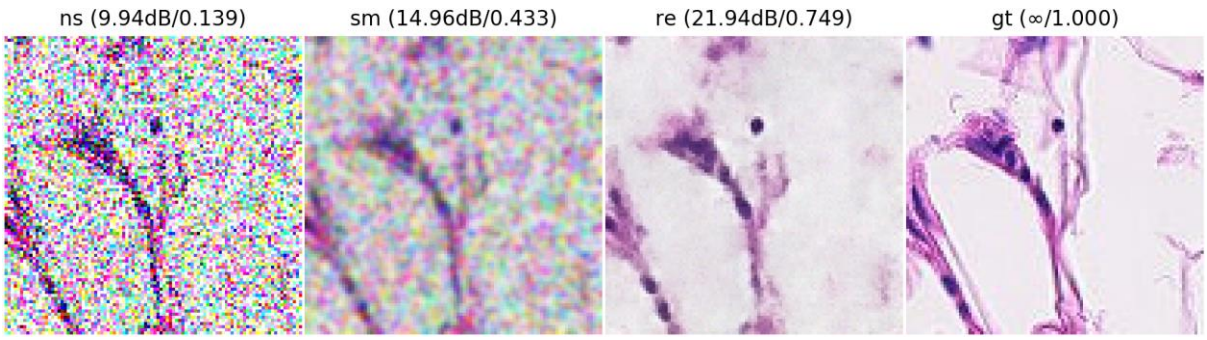

Figure 1: Noisy input image (ns) compared to a smoothed (sm), restored (re) and ground truth (gt) version. The metrics shown are the peak signal-to-noise ratio [dB] and structural similarity index.

References

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