Computational Super-resolution Imaging with Multimode Fiber Using Optimized Illuminations

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ABSTRACT

Imaging through a multimode fiber (MMF) with a spatial-resolution beyond the diffraction limit has recently been demonstrated using computational super-resolution methods. We performed a modelling study to assess the performance of a compressed image reconstruction algorithm, Basis Pursuit, using different illuminations. In addition to the increased speed due to the reduced number of measurements, we characterized other potential benefits with respect to robustness to noise and resilience to fiber bending when using compressed imaging with optimized illuminations.

Keywords: Multimode fiber, Computational imaging, Endo-microscopy, Illumination

1. INTRODUCTION

An optical microscope is capable of imaging sub-cellular structures and dynamic processes in a living organism, making it a core device used in biological research. As the process of optical imaging is the convolution of the original object and the point spread function (PSF) of the system, the wave nature of light limits the resolution of such optical microscope, often referred to as diffraction barrier.[1] The advent of super-resolution microscopy has effectively overcome the diffraction barrier, thereby leading to significant improvement in spatial-resolution.[2–4] Moreover, computational imaging has recently gained popularity as an alternative way to obtain super-resolution images by image post-processing.[5,6] Thus, the methods to obtain images with extended spatial-resolution may be broadly divided into two categories, namely, instrumental super-resolution and computational super-resolution.[5,7] The instrumentation super-resolution is mainly based on engineering the PSF of the corresponding optical system such that a small and sharp spot size is obtained.[8] This method is also often referred to as optical super-resolution[9] or hyper-resolution.[10]

Computational super-resolution is achieved primarily by image post-processing, using a priori knowledge of the illumination and a probabilistic reconstruction process (iterative optimization of a cost function).[5,11] Deconvolution and compressed or compressive imaging are two of the most common computational super-resolution methods. Deconvolution is a mathematical process to reverse an image distortion based on the given acquired image, knowledge of the degradation model and the associated noise.[12] Compressive imaging on the other hand, is an effective mathematical framework which has the ability to acquire as well as effective in reconstruction of a particular signal with a minimum number of measurements. This is doable when the signal of interest is highly compressible or sparse in some basis with a relatively small or zero-valued coefficients, enabling efficient signal reconstruction through the implementation of a proper reconstruction algorithm.[13–15] The principle idea behind compressive imaging is that, with the use of prior knowledge about the signal′s sparsity, just a few samples can be used than those dictated by the Nyquist-Shannon theorem to reconstruct a signal.[16]

In general, both the instrumentation and computational super-solution methods have been demonstrated to be useful in a number of scenarios. However, in practicality some instruments are less amenable to physical methods. For instance, super-resolution imaging through a multimode fiber (MMF) has only been demonstrated with deconvolution[17] and with compressed imaging[18] methods so far. A typical MMF based endo-microscopy system mainly exploits the idea of scanning fluorescence microscopy and needs to be calibrated by acquiring a

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transmission matrix (TM) using an interferometric arrangement at the distal end of the MMF such that a focus spot is formed.[19] The object on the fiber distal facet is reconstructed by digitally scanning the focus spot (by updating the wavefront) for each location, or pixel, and the fluorescence is collected by a point detector. This is a time-consuming process as the sampling rate must follow the Nyquist criterion and there is every possibility that the fiber will be perturbed during this process. In such a situation, the TM is no longer valid[19, 20] and the fiber needs to be re-calibrated which significantly limits the flexibility and application of the current MMF based endo-microscopy systems. The main advantage of using compressive imaging in a MMF based endo-microscopy system is that it only requires fewer measurements (sparse sampling, below the Nyquist criterion) than that for a point scanning system, thus, providing a substantially increased speed and extended spatial-resolution.[18]

The compressive imaging and deconvolution are similar in the sense that they both try to solve an ill-posed problem in an iterative way whereas the difference between them lies in the fact that the former involves a series of speckle patterns (speckle illumination basis) whereas the latter typically involves a sequence of foci (foci illumination basis) as an illumination basis. Compressive image reconstruction works better in the case of randomized sensing where data is obtained from all parts of an object in a pseudo-random manner.[14, 21, 22] However, its working is restricted by the type of illumination used, which suggests that the use of individual foci with uniform separation such as the ones used for deconvolution can be used as the illumination basis in compressive imaging. This sampling strategy has a number of advantages, such as, it is commonly used by a number of point-scanning optical microscopy systems and there is lack of biasedness for estimators it produces.[23]

In the present work, we perform a modelling study to characterise the performance of computational super-resolution imaging in a MMF based endo-microscopy system using foci and speckle illuminations. Foci illumination consisted of a sequence of diffraction-limited focus with uniform separation, whereas, speckle illumination consisted of a sequence of unique speckle-like intensity distribution. Two important situations in an MMF based endo-microscopy system were modelled where the effect of noise and the impact of external perturbation were analysed on the quality of compressive image reconstruction using both the illuminations.

2. METHODOLOGY

The process of implementation of computational super-resolution imaging in a simulated MMF based endo-microscopy system using compressed imaging is explained briefly. We initially generate two illumination bases, foci and speckle illuminations corresponding to light propagation in a MMF. A sequence of diffraction-limited proximal foci were created and then by evaluating the transmission matrix and taking its regularized inversion, the foci illumination was generated at various lateral positions in the sample. For foci illumination, a proximal grid of 49×49 pixels and a distal grid of 120×120 pixels were used for the simulation. The resulting illumination matrix was then sub-sampled to select 2401 foci, uniformly covering the sample over the surface of the core. Next, speckle illumination was generated using the transmission matrix and a sequence of diffraction-limited foci at the proximal end of the MMF. The speckle illuminations are a result of the scrambled field due to mode coupling in the MMF, corresponding to a sequence of diffraction-limited foci at different location of the MMF proximal end. A proximal and distal grid of 120×120 pixels were used for the speckle simulation. The resulting illumination was then sub-sampled to 2401 illuminations uniformly covering the proximal core area.

The foci and speckle illumination bases are used to illuminate the sample which in this case is generated by simulating an array of 2D points at random locations, resembling 2D bead objects. An array of 2D points at random locations were produced using salt & pepper noise function having a density of 0.001 on a null matrix with dimension 120 × 120, to simulate the 2D bead objects. The position of the beads was confined within a definite region by defining a particular radius from the center of the image. Thereafter, a Gaussian distribution ($\sigma = 0.5$) was used to randomise the intensity of the beads and subsequently a Gaussian filter ($\sigma = 1.33$) was used to define all the beads with the same diameter. The signal which is supposed to be generated after illuminating the object (beads) is calculated by integrating the matrix value generated as a result of pixel-wise multiplication of the respective illuminations (foci and speckle) and the object, in order to resemble the light detection by a photomultiplier tube (PMT) in an endo-microscopy system. A compressed noisy signal was generated by adding varying amounts of zero-mean Gaussian white noise with a specified variance to the bead objects in order to study the impact of noise on super-resolution image reconstruction methods.

Further, we consider more specific situation in an endo-microscopic system where the MMF is often affected by perturbations. The perturbation introduced here is bending. In the case of a bent MMF, the transmission matrix calculated or the calibration performed is no longer valid and consequently the focus spot or the speckle patterns get distorted or changes. Corresponding to these changes, the modification in illumination was simulated with different values of bent radius and the subsequent steps are performed as mentioned above. For bending, the signal was calculated by pixel-wise multiplication of the bent illumination and 2D sample for a particular illumination and then integrated.

Next, we perform compressive image reconstruction by using the basis pursuit[24] algorithm (with maximum number of iterations set to 3000, augmented Lagrangian value set to 1 and over-relaxation parameter set to 1) that generates super-resolution images with high reconstruction accuracy. The 2D bead objects that have been simulated are represented as a 1D vector (say x) with a set of M 2D $N \times N$ speckle and foci illumination patterns as illumination matrices, where $M \ll N^2$, meaning the vector x is under-sampled. Finally, we perform quantitative analysis to compare the accuracy of reconstructed super-resolution image say, B with that of the object say, A by calculating the correlation coefficient (R). For all the analysis, light at 532 nm was modelled passing through an MMF having a diameter of 50 μm, a numerical aperture of 0.22 and a length of 1 m. Normalisation was applied such that the total intensity was the same for both illumination strategies. For bending, a single fiber segment was considered with a curvature defined by a bending radius (ρ).[25] The light propagation through an MMF is considered based on the model decribed in Plöschner *et al.*[19] and the original Matlab code (for MMF simulation) that has been modified as per our requirements can be assessed at.[25]

3. RESULTS AND DISCUSSION

3.1 Effect of noise

In an MMF endo-microscopy system, when the signal is poor then it introduces noise as the signal to noise ratio is very small. Thus, to analyse the effect of noise on the image reconstructions using basis pursuit algorithm, we use foci and speckle illuminations with varying amount of Gaussian white noise. To illustrate this, we have performed the modelling to generate light propagation through the MMF as mentioned earlier and a noisy signal was generated. This was done by integrating the matrix values resulting from the pixel-wise multiplication of foci and speckle illuminations with that of the object and then adding Gaussian white noise with specified values of variance. Figure 1(a) and Fig. 1(b) demonstrates super-resolution image reconstruction (it is to be noted that the ability to obtain super-resolution images with compressive imaging using foci and speckle illuminations has been simulated, although the results are not presented here) using foci illumination and speckle illumination, respectively, corresponding to a noisy signal obtained by adding an equivalent amount of noise ($\sigma = 10^{-11}$) as discussed in the methodology section 2. Figure 1(c) shows a plot of correlation coefficient R of the reconstructed image with that of the ground truth object as a function of varying amount of noise.

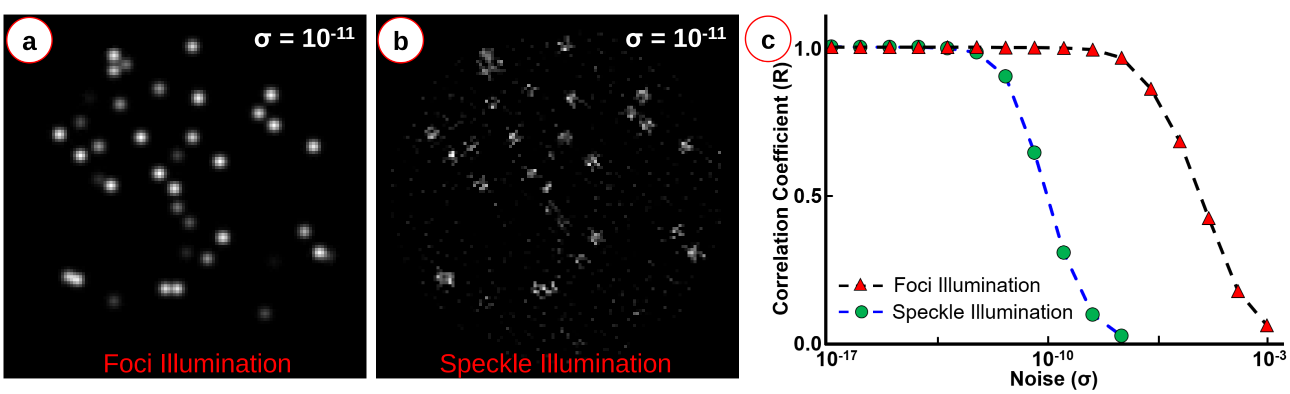

Figure 1. Example super-resolution images of 2D beads reconstructed with the same amount of Gaussian white noise ($\sigma = 10^{-11}$) using the basis pursuit algorithm with (a) foci illumination and (b) speckle illumination and the correlation coefficient plot (R) between the reconstructed image and the ground truth object as a function of noise for both the illuminations. Image width: 54.5 μm.

From Fig. 1(a) and Fig. 1(b) it is clear that the compressive image reconstruction using foci illumination is better in comparison to speckle illumination where the bead images seems distorted. This is also evident from the correlation coefficient plot R where the line plot for foci illumination drops off more slowly than the speckle illumination, thereby indicating that foci illumination is much more robust to noise.

3.2 Resilience to MMF bending

A common implementation of an MMF based endo-microscopy system involves shaping the wavefront, entering the proximal end of the MMF such that a focus is formed at the distal end or the imaging plane, where the sample is located.[26,27] The focus can be digitally scanned over the object by updating the wavefront for each location, or pixel, and the fluorescence is collected by a point detector. The required wavefront can be determined by performing a calibration that acquires a transmission matrix (TM), which describes the complex transformation between the two planes.[28,29] The TM will no longer be valid if there is any perturbation in the MMF[19,20] and it needs to be updated which is a very time-consuming process and difficult to do in real time. Here, we analyse the impact of bending on compressed imaging reconstruction for both foci and speckle illumination by considering different bending radii (ρ), to illustrate if a particular illumination is more robust to bending than the other. Simulations were performed to first generate illuminations through a straight fiber and when the fiber is bent by considering various bending radii as the process described in methodology section 2. Figure 2(a) represents the super-resolution 2D bead image reconstructed using the basis pursuit algorithm with foci illumination, whereas, Fig. 2(b) represents similar image reconstructed using speckle illumination, both having the same bending radius (ρ = 10 m), respectively. Figure 2(c) represents the correlation coefficient plot R between the reconstructed image and the ground truth object as a function of inverse bent radius ($\frac{1}{\rho}$).

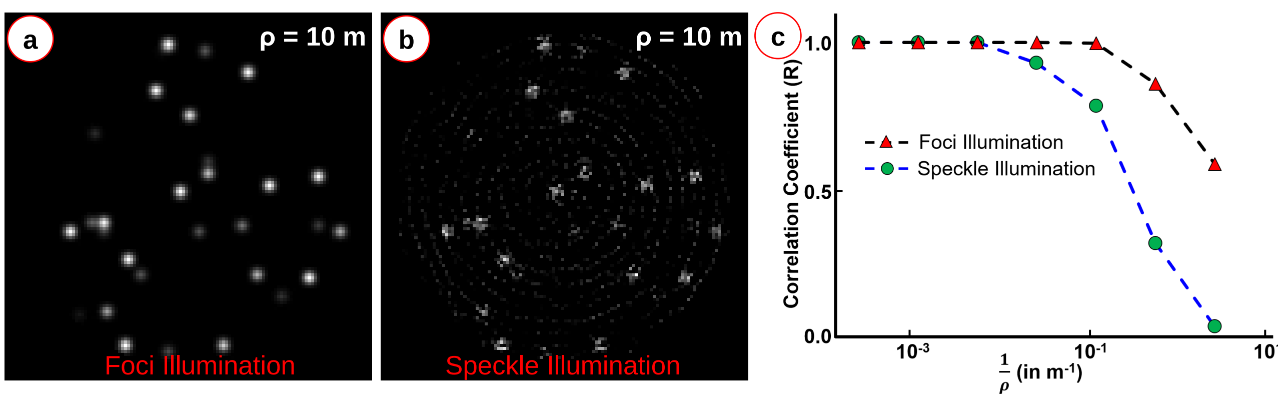

Figure 2. Example super-resolution images of 2D beads reconstructed with the same bending radius ($\rho = 10$ m) using the basis pursuit algorithm with (a) foci illumination and (b) speckle illumination and the (c) correlation coefficient plot R between the reconstructed image and the ground truth object as a function of $\frac{1}{\rho}$ for both the illuminations. Image width: 54.5 μm.

From Fig. 2(a) and Fig. 2(b) it is clear that the super-resolution compressive image reconstruction using foci illumination is more resilient to bending than speckle illumination. This is also clear from the correlation coefficient plot (Fig. 2(c)) where the value of R drops off at a much smaller bending radius for foci illumination in comparison to that of the speckle illumination. It is also to note that the foci illumination retains its shape even in the presence of perturbations when compared to speckle illuminations and this could eventually lead to applications for a large variety of perturbations.

An optical illumination basis should ideally have minimum coherence for a sparse object distribution in a Cartesian object space.[30] This has been validated in the present work where illumination of the sample sequentially with equidistant foci is found to be much more efficient than using randomly generated speckle patterns. This process of using equidistant individual foci for illumination is known as systematic random sampling. Such a process is considered to be stochastic under the condition that the origin of the illumination grid is randomly selected[23] and it can provide faster convergence towards expected statistical properties than other random sampling configurations.

It is noteworthy that the advantages associated with foci illumination in compressed imaging can be achieved in any optical point-scanning system. This was shown with a one-photon endo-microscopy with MMF but can be easily achieved with other endo-microscopy systems, such as, confocal or multiphoton, as these advantages are characteristics of the illumination basis. This fact also implies the generalisability of the method to any compressed imaging algorithm.

An important challenge in the field of MMF based endo-microscopy is the ability to modify the illumination pattern with bending of the fiber.[19,20,31] Some of the approaches proposed so far to compensate for bending include numerical solutions based on the fiber deformation information, measuring the transmission matrix using distal probes/detector, etc.[19,32,33] These approaches when combined with foci illumination (which is much more robust to bending than speckle illumination) will not only lead to application of MMF based endo-microscopy in fiber perturbation but also obtain super-resolution computational imaging at the same time.[18,34–36]

4. CONCLUSION

In conclusion, we have successfully demonstrated the implementation of compressive imaging in an MMF based endo-microscopy system and analysed its performance in a couple of important situations using foci and speckle illuminations. The use of foci illumination renders several advantages over speckle illumination for compressed imaging such as increased robustness to noise and greater resilience to external perturbations (such as bending). All these advantages are a consequence of illumination in a sparse Cartesian object space, independent of the compressive algorithm used or the method of generation of foci. Thus, the use of compressed imaging with foci illumination is much more efficient and is expected to be applicable in several diffraction-limited optical imaging systems.

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