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Parametric point-spread-function model optimization for microscopic image super-resolution

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Image resolution degrading problems can roughly be classified into two groups, diffraction limit and optical aberrations. In general, the image resolution is limited by the optical diffraction limit. Again, optical aberrations induced by the lenses can also lead to severe image blurring or quality degradation. The article presents a novel image deblurring algorithm by proposing a new parametric point spread function (PSF) estimation in a modified Wiener deconvolution process. The optical PSF is first modeled using a JINC-liked function by considering linear-spatial invariant aberrations and imaging parameters. An iterative Wiener deconvolution algorithm is used to optimize the quality of test images. The test image's coefficient of variance (CV) is set as the objective function for model optimization. Furthermore, to minimize undesirable ringing artifacts and noise amplification that may be generated in the above process, the gradient map density and CV of the image gradient map are proposed and developed for the regularization terms. Since pixel-wise deconvolution operation may suffer color distortion, a multi-channel parametric fitting method for image color correction is also applied. In addition to using JINC function as the PSF estimated basis model, we also take other types of function to model the PSF which introduce more freedom degrees for the modeling. By testing the developed method on some microscopic biomedical images, the experimental results show that the proposed method can effectively restore image detail information and improve the sharpness while maintaining the chrominance and chroma of the test images. As seen from the test as a preliminary verification, image super-resolution can be achieved by the developed method.

1. Introduction (Times New Roman 10pt)

The finite pupil size and aberrations limit the resolution of the imaging system. By analyzing the point spread function (PSF) and modulation transfer function (MTF), we can figure out the imaging system's theoretical resolution. When the lens group design of the microscopy is known, we can simulate the imaging system with some simulated optical software. In Zemax, they assume each point on a wavefront as an ideal point light source that radiates a spherical wavelet. The diffraction of the wavefront as it propagates through space is given by the interference of all the aspherical wavelets radiated. Also, we can model the imaging system by diffraction theorem and the Huygens-Fresnel principle[1], which will be the theoretical solution. Once we can got the PSF of the system, we can do the deconvolution with the blurred image and finally got a clear one. Recently, machine learning has been used for the image deconvolution process and got an outstanding result [2-4]. However, sometimes we don't know the specific system design. Even if we can get the specific system design and simulate it, there still exists some uncertainties during imaging, like the dark current in CCD, turbulence and the deformation of the lenses, etc. Blind deconvolution can efficiently solve the problem. We can estimate the imaging system's PSF from single or multi-images by solving the inverse problem. How to model the PSF 'inside' the image is an ill-posed problem. Some researches model the PSF with Gaussian function [5-7], these kinds of methods can generally model the PSF but lack the physical meaning. Some researches use the more complex model to estimate the PSF model. However, these researches mostly focus on specific fields[8, 9], which means the physical models of PSF between them would be different. Besides, most of them do not take aberration into account. However, it cannot always be sure that the optical imaging system can be an aberration-free system.

We proposed parameterizing the PSF model which based on diffraction theory and performing the Wiener-based deconvolution[10] process with the optimization method. By analyzing and iterating the implicit parameters of the PSF, we can model and fit the actual PSF of the imaging system. For the diffraction limit induced by the finite pupil, considering most of the imaging systems are composed of circle lenses, we take the JINC-liked function to model the diffraction-limited PSF.

We introduce Seidel coefficients as the optical path (phase) parameters for the aberrations, which will deform the diffraction-limited PSF. Last, considering other uncertainty factors, we proposed using linear gain, nonlinear gain, and bias as global system adjustment parameters. With the three types of parameters above, we can physically model the PSF.

To restore the high-frequency information of the image while avoid the noise amplification and ringing artifact during the deconvolution process, a well objective function design is necessary. Our objective function is defined as minimizing the coefficient of variance (CV) of the deconvolved images' intensity and defines two regularization terms as the energy density of the first order gradient map and the CV of the first order gradient map. By adjusting the coefficients of regularizing terms, the design can restore the high-frequency information while suppressing the noise and ringing artifacts.

2. Simulation

Before estimating the PSF, it's necessary to consider the resolution of the blurred image. If the image resolution is too low, we should estimate the PSF with a small matrix, which means the low resolution of PSF leads to poor deconvolution results. In view of this, we will up-sample the low-resolution image to over 1200 x 1200 pixels and estimate the PSF with a 127 x 127 pixels matrix. A bigger matrix size should be considered when the image is severely degraded. We believe that the chrominance and the chroma of the image before and after blurring should be similar, so we retain the Cb and Cr channels of the blurred image, an only process in the Y channel.

Error! Reference source not found. shows the simulation and the comparison of the mouse primary microglia cell, alpha-tubulin image which credit to CrestOptics[11]. The top-left figure is the result form the conventional confocal microscopy. The top-right figure is the result form CrestOpttics' DeepSIM microscopy[11]. The bottom-left one is our result which took the confocal result to operate the deconvolution process, and the bottom-right one is the corresponding estimated PSF.

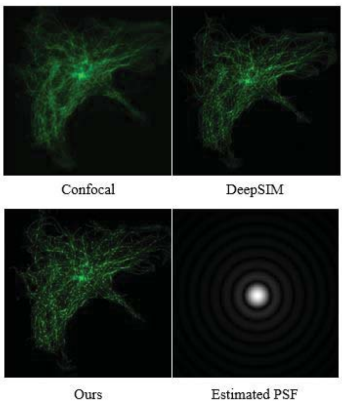

Fig. 1 The simulation and the comparison of the mouse primary microglia cell, alpha-tubulin image.

In addition to taking the JINC function as the PSF basis function, we also experimented with five different models, including the Sinc function, raised cosine function, Gaussian function, Mexican hat function and the decay-Dirichlet function. These functions have low-pass, roll-off, periodic, and varying idempotent properties, which can provide higher flexibility of the fitting process.

Error! Reference source not found. shows the simulation which based on the five different models. The left figure is the deconvolution result and the right figure is the corresponding estimated PSF. We can find that these models can achieve a good image quality with the proposed deconvolution operation.

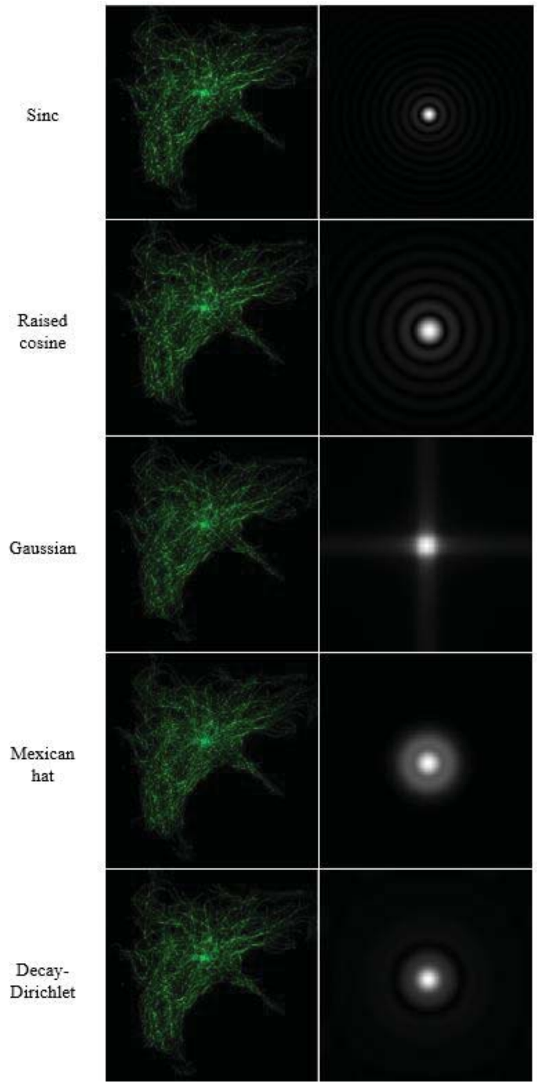

Fig. 2 Deconvolution simulation with five PSF estimated models.

Error! Reference source not found. shows the simulation of the image of the fixed BPAE cells labeled with Alexa 488-phalloidin (actin) and mitotracker CMXRos (mitochondria) from confocal microscopy[12]. Through the experiments, we also found that those models which have low power or low periodicity have the poor fitting ability, such as the Gaussian and Mexican hat functions. In contrast, models with higher power perform better, such as Raised cosine[13] and Decay-Dirichlet.

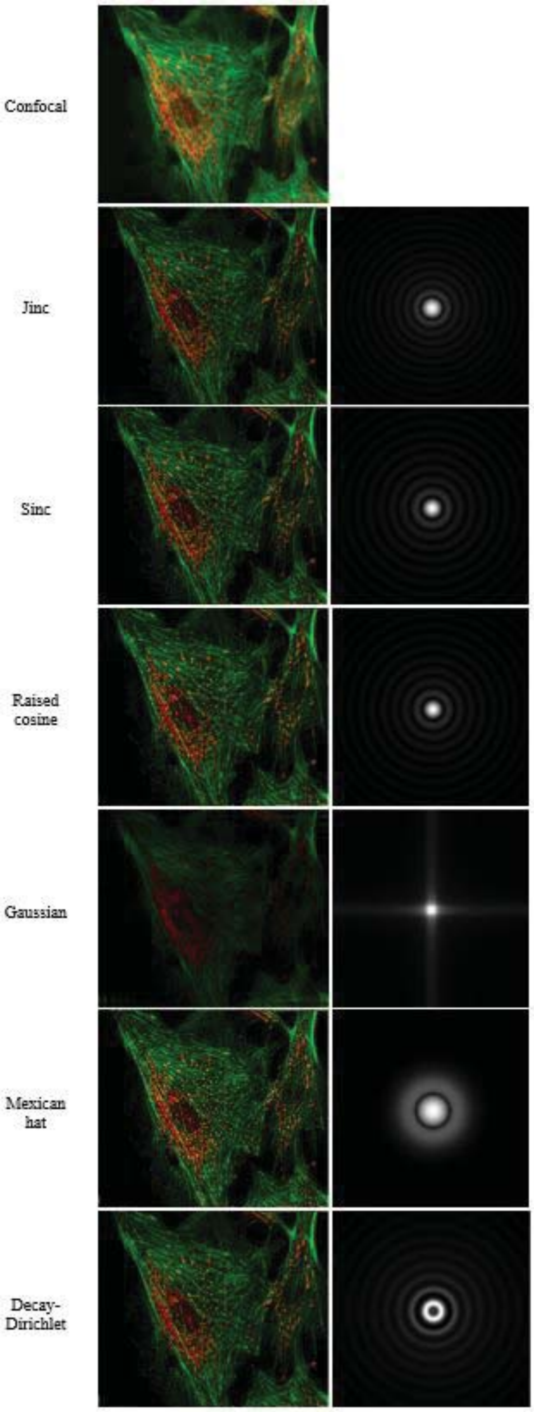

Fig. 3 Comparison of original confocal image and ours result with different PSF estimated models.

3. Conclusions

We propose a super-resolution method for imaging systems by parameterizing the point spread function of the imaging system. We considered the diffraction pattern of the imaging system which include the diffraction-limited PSF pattern, aberrations, and other factors, we take these parameters to model the physically point spread function of the microscopy. The optimization algorithm will iterate the estimated PSF to fit the real one by deconvolving with the blurred image. In addition to modeling the theoretical solution (JINC function), we also take other functions with varying properties for simulation and comparison. It can be seen from the results that our method can effectively restore high-frequency information and successfully remove the blurring. In the future, we will take machine learning technology into our research which aims to build a model-based super-resolution model and apply it to optical inspection.

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