Optics Communications ▮ (▮▮▮▮) ▮▮▮–▮▮▮

Contents lists available at ScienceDirect

Optics Communications

journal homepage: www.elsevier.com/locate/optcom

Adaptive denoising method for Fourier ptychographic microscopy

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A R T I C L E I N F O

Keywords:
Fourier ptychographic
Adaptive denoising
Difference matrix
Data redundancy

A B S T R A C T

Fourier ptychographic microscopy (FPM) is a recently developed wide-field and high-resolution (HR) imaging technique, reconstructing HR spectrum from a series of low-resolution (LR) images at different illumination angles. Although many significant progresses have been made in FPM in the past few years, imaging noise is still an inevitable problem, which could seriously distort the results recovered using the conventional Fourier ptychography approach without image preprocessing. Generally, before FPM reconstruction, a thresholding denoising method is usually employed to eliminate the noise. However, conventional thresholding denoising algorithms cannot differentiate useful signals from imaging noise effectively, thus these algorithms usually eliminate signals and noise simultaneously. Here we propose an adaptive denoising method for FPM, which takes advantage of the information redundancy in FPM to separate signal from noise during the recovery process without any pre-knowledge about the noise statistics. Simulation and experimental results are presented to evaluate the performance of the proposed method. It is demonstrated that this method can both improve the accuracy and robustness of FPM and relax the imaging performance requirement for implementing high-quality FPM reconstruction.

1. Introduction

Fourier ptychographic microscopy (FPM) is a recently developed wide-field and high-resolution (HR) imaging technique [1], which utilizes angularly varying illumination and a phase retrieval algorithm to surpass the diffraction limit of the objective lens [2–8]. Similar to the conventional ptychography approaches [9,10], FPM shares its roots with phase retrieval algorithm [2–8] and synthetic aperture imaging [11–16]. In a typical FPM imaging system, a fixed-position LED matrix is used for angle-varied illuminations. At each illumination angle, a low-resolution (LR) intensity image of the specimen, with the resolution determined by the numerical aperture (NA) of the objective lens, is recorded. The recorded LR images from different illumination angles can be iteratively stitched in the Fourier domain to recover a HR complex image of the specimen. The final reconstruction resolution is determined by the sum of the NA of the objective lens and the largest incident angle of the LED matrix.

In order to improve the imaging performance of FPM, a series of improved algorithms have been proposed lately. Some of them improve the reconstruction accuracy and the recovery resolution of FPM [17–24], and others reduce measuring time of FPM imaging process and improve data acquisition efficiency [21,25–29]. However, imaging noise is still an inevitable problem, which distorts high-frequency details and stains the background of the recovered image [30]. Although several of the methods described above, such as the Wirtinger flow optimization and the adaptive step-size [20,29], suppress the image noise from the final reconstruction results, they are achieved by means of improving the FPM convergence properties and not really eliminate noise in captured images. Take the example of the Wirtinger flow optimization algorithm, this method generally reside on expensive processing requirements, making it less appealing from a computational point of view.

Generally, better quality images not only improve the accuracy of FPM, but also improve its convergence speed. So, before FPM reconstruction, a thresholding denoising method is usually used to eliminate the noise in the initial data [21]. In the conventional thresholding denoising method, a fixed threshold for denoising is generally obtained by calculating the average intensity of the background of the dark-field image. However, the main drawback of this method is that it cannot differentiate useful signals and imaging noise effectively, thus these algorithms usually dislodge signal and noise simultaneously. Thus, there

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http://dx.doi.org/10.1016/j.optcom.2017.05.026
Received 22 March 2017; Received in revised form 11 May 2017; Accepted 13 May 2017
Available online xxxx
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is a trade-off between the resolution of the HR image and the denoising effect in FPM.

As reported in [28], a key aspect of a successful FPM reconstruction is the data redundancy requirement of the recovery process. Precisely, such a data redundancy requirement is very important for recovering the lost phase information of the specimen. At least 35% aperture overlapping percentage in the Fourier domain is required for an accurate reconstruction of both intensity and phase information in FPM. Moreover, the FPM reconstruction result will not change significantly when the percentage of empty pixels in the image is less than aperture overlapping percentage in the Fourier domain. Based on the above considerations, we propose an adaptive denoising method for FPM, which takes advantage of the data redundancy in FPM. Different from the conventional thresholding denoising method, the adaptive denoising method introduces a difference matrix to separate signal from noise during the recovery process without any pre-knowledge about the noise statistics. In addition, we investigate the characteristic of the difference matrix to implement the adaptive updating of the denoising method. Simulation and experimental results are presented to evaluate the performance of the proposed adaptive denoising method and it is demonstrated that this method can both improve the accuracy and robustness of FPM and relax the imaging performance requirement for implementing high-quality FPM reconstruction.

2. Principle of FPM and adaptive denoising method

2.1. Principle of FPM

Before introducing the principle of the adaptive denoising method, it is worthwhile to review the basic concepts of FPM. As detailed in [1], a typical FPM platform consists of a LED matrix and a conventional microscopy with a low NA objective lens. We sequentially turn on single LED element in the matrix to illuminate the 2-D thin specimen from different angles and capture the corresponding LR intensity image. Since the 2-D thin specimen is illuminated by plane waves with different angles, the spectrum of the specimen on the back focal plane of the objective lens is shifted to the corresponding different positions. Thus, some of the frequency components that are beyond the NA of the objective lens are shifted into that is within the objective lens NA, so that they can be transferred to the sensor plane for recording. Then, these captured LR images are sequentially iterated in the Fourier domain to update the spectral information in the corresponding sub-region. The adjacent sub-regions overlap with each other, which extends the space-bandwidth product (SBP) and restores high-frequency information that exceeds the spatial resolution of the objective lens. Eventually, the HR intensity and phase image of the specimen are reconstructed simultaneously.

There are five steps in the reconstruction process of traditional FPM technology. First, initialize the HR complex amplitude distribution U_0 with amplitude of the LR image corresponding to the vertically incident plane wave. This HR complex amplitude distribution is used to generate multiple LR target images corresponding to different illumination angles. Second, the spectral information in a certain sub-aperture of the initial HR spectrum U_0 is intercepted to produce a LR complex amplitude distribution, which is called the target complex amplitude distribution $\sqrt{I_{mt}}e^{i\varphi_{mt}}$ (m represents the serial number of the captured images). Third, maintain the phase of the target complex amplitude image unchanged and update the amplitude portion $\sqrt{I_{mt}}$ of the target complex amplitude image $\sqrt{I_{mt}}e^{i\varphi_{mt}}$ with the actual measurement $\sqrt{I_{mc}}$ at the corresponding illumination angle, and finally we will get the updated complex amplitude distribution $\sqrt{I_{mc}}e^{i\varphi_{mt}}$. Fourth, the spectrum $u_m(k_{mx}, k_{my})$ of the updated target complex amplitude image $\sqrt{I_{mc}}e^{i\varphi_{mt}}$ is obtained by using the Fourier transform, which is used for updating the spectral components within the corresponding sub-aperture of the HR spectrum. Fifth, this replace-and-update sequence is repeated for all incident angles, and the fifth step is iterated several times until the solution converges.

In traditional FPM iteration process, the captured LR images are directly denoised using a fixed threshold. This fixed threshold is generally obtained by calculating the average intensity of the background in the dark-field image. However, an unavoidable problem in this denoising method is that it cannot distinguish noise from useful signals. This problem is very noticeable in the denoising of the dark-field image, because a large number of useful signals are usually weaker than the noise in dark-field image, and this means that these useful signals will be eliminated easily by using a fixed threshold denoising method. Fig. 1 shows the denoising results for a dark-field image with different denoising methods. As shown in Fig. 1(c), after using the conventional fixed threshold denoising for the dark-field image, the noise of the dark-field image is eliminated, but a large number of effective signals are also eliminated. Eventually, such a loss of information will result in the lack of details of the FPM reconstructed HR image.

2.2. Adaptive denoising method

In order to effectively eliminate the noise in captured images, a noise discrimination factor is introduced to the third step of the above process to differentiate useful signals and noise approximately, which is expressed as $C_m = \sqrt{I_{mc}} - \sqrt{I_{mt}}$. It can be seen that the updated image distribution $\sqrt{I_{mc}}e^{i\varphi_{mt}}$ can also be expressed as $(C_m + \sqrt{I_{mt}})e^{i\varphi_{mt}}$. It is not difficult to find that C_m is a matrix which has the same size as the captured image, and its values represent the difference between actual amplitude $\sqrt{I_{mc}}$ and the amplitude portion $\sqrt{I_{mt}}$ of the target complex amplitude image $\sqrt{I_{mc}}e^{i\varphi_{mt}}$ at the identical illumination angle. In the ideal noiseless case, the values of the C_m matrix mainly concentrate within a small vicinity around 0. Conversely, with the noise increasing in captured images, the values of the C_m matrix depart from 0 gradually. Based on these premises, the matrix C_m can be used to differentiate useful signals from noise pixel by pixel approximately. Specifically, if the value of a pixel in matrix C_m is almost close to 0, it indicates that the pixel tend to be noise. On the other hand, if the value of a pixel of matrix C_m is far away from 0, it means that the pixel is more likely to be noise.

Based on the above knowledge, the adaptive denoising process of images can be seen as making the value of the C_m matrix as close as possible to the ideal noise-free situation. The process of FPM reconstruction using the adaptive method is shown in Fig. 2. First, similar to the traditional FPM refactoring, it starts with a HR complex amplitude distribution of the specimen profile: U_0. Second, produce target complex amplitude distribution $\sqrt{I_{mt}}e^{i\varphi_{mt}}$. Third, solve the difference matrix $C_m = \sqrt{I_{mc}} - \sqrt{I_{mt}}$ to differentiate noise from useful image signals, and update the values of the matrix by setting the value of the C_m matrix which is far away from 0 to 0. The updated matrix $C_{m_{update}}$ is obtained as a denoising factor. Fourth, the denoising matrix $C_{m_{update}}$ is used to update the intensity components of the target images, while the phase components remain unchanged, the resulting complex amplitude distribution is $(C_{m_{update}} + \sqrt{I_{mt}})e^{i\varphi_{mt}}$. Fifth, the updated complex amplitude distribution is used to modify the corresponding spectral regions of the HR complex amplitude distribution U_0. Lastly, this replace-and-update sequence is repeated several times until the solution converges. Fig. 1(d) shows the dark-field image using the adaptive denoising method. The image not only eliminates the noise, but also preserves more useful signals of the image compared with Fig. 1(c).

In the iterative process including adaptive denoising method, there is a step that needs to be discussed, that is, the initialization of the FPM iterative process. For FPM technology, it is common to use a LR bright-field image to initialize the HR spectrum, but as a phase retrieval algorithm, using a constant to initialize can also get the correct convergence results. In the adaptive denoising method, the selection of the initialization step can be discussed in different cases. In the first case, all LR images are captured for adaptive denoising. In this case, a LR bright-field image must be used to initialize, since this ensures that the obtained C_m matrix can distinguish between noise and useful signals. In