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Multi-distance phase retrieval with a weighted shrink-wrap constraint

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ABSTRACT

Multi-distance phase retrieval enables a full wavefront recovery with a set of defocused intensity patterns. However, the convergence speed of multi-distance phase retrieval is restricted by a stagnant issue, which leads to a low imaging contrast for visual observation. We propose an acceleration scheme to solve this problem. A shrink-wrap constraint is imposed to obtain an efficient support region. In support region, a weighted feedback strategy is used to speed up the convergence. In non-support region, an attenuated term is introduced to eliminate redundant data. With this combined constraint, imaging contrast and convergence speed are both enhanced observably. Simulations and experiments demonstrate the validity of this acceleration scheme in a lensfree imaging system. The proposed method can both reduce the workload of experimental data acquisition and computational load.

1. Introduction

Iterative multi-distance phase retrieval (MDPR) could reconstruct a wavefront with a series of defocused intensity observations, which has been applied to lensfree on-chip microscope [1,2], quantitative phase imaging [3], aberration estimation [4], 3D imaging [5] and optical encryption [6]. Compared to conventional digital holography [7,8], it does not need an extra reference beam, and thus enables a low-cost, compact and large field of view hardware for lensfree imaging [9]. Also, if the procedure of phase retrieval is identified as a solution of optimization problem, the robustness and stability of multi-distance phase retrieval could be further enhanced with the use of nonconvex alternating projection optimization [10–12].

In lensfree on-chip microscopy, MDPR takes the task of complex-valued image reconstruction and pixel super resolution breaks the pixelated limitation resulting from an imaging sensor. To get subpixel component, pixel super resolution [13] needs to introduce a lateral shift grid (6×6 or 8×8) at each diffraction distance. Thus a 3D-stack data is necessary to get a clear and perfect image recovery for lensfree multi-distance imaging. If the measurement times of multi-distance data is reduced, data storage capacity and device complexity will be decreased. However, a lower measurement times of diffraction pattern could lead to a stagnant issue for phase retrieval. Hence it is critical to seek an acceleration scheme for portable and low-cost lensfree implementation.

In MDPR, amplitude-phase retrieval (APR) algorithm has been proven to perform a stable and robust image reconstruction than other MDPR methods [14,15]. However, its weak convergence is still evident under lower measurement times. A better retrieved image needs more iterations, which could be time-consuming for computation. In our previous work [16,17], a weighted feedback strategy is proposed to speed up the convergence of APR algorithm. However, weighted feedback strategy is sensitive to measurement times. For example, if the recording number is 2, weighted feedback strategy will become slowly convergent. Also, it is easy to magnify the background noise while enhancing the imaging contrast.

In this work, we combine shrink-wrap constraint [18] with weighted feedback strategy to form a new acceleration scheme. In this scheme, the limitation of weighted feedback strategy is broken down. A shrink-wrap constraint is used to provide a proper support region and weighted feedback strategy is merely employed in this support region. In non-support region, an attenuated term is employed to eliminate redundant data. Simulation and experiment prove that our method is capable of achieving a better imaging effect on the convergence speed and imaging contrast in comparison with other acceleration methods.

2. Method and simulation

Our acceleration scheme is composed of three components: APR method, shrink-wrap constraint and weighted feedback strategy. This paper focuses on the lensfree imaging and all computations are defined in free space diffraction model. The workflow of standard APR method follows: (1) an object function O^k is initialized with a constant matrix; (2) the kth object estimation is propagated forward to different measuring planes and a dataset of diffraction patterns $C_n^k (n \in [1, \mathrm{N}])$ are recorded by moving a CCD camera along optical axis. The index n corresponds to the nth diffractive distance and a forward model calculation is done by $\mathbf{F}^{-1}[\mathbf{F}(O^k)H_{Z_n}]$, where $\mathbf{F}$ and $\mathbf{F}^{-1}$ denote Fourier transform and its inverse mode, H_{Z_n} is an angular spectrum transfer function and $Z_n (n \in [1, \mathrm{N}])$ are different diffractive distances; (3) replacing the ampli-

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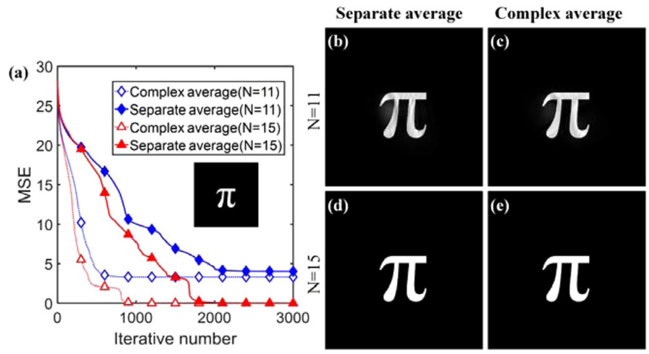

Fig. 1. The simulation of different average operations for APR method. (a) convergence curve; (b) and (d) are retrieved objects for separate average operation with 11 and 15 measurements; (c) and (e) for complex average operation.

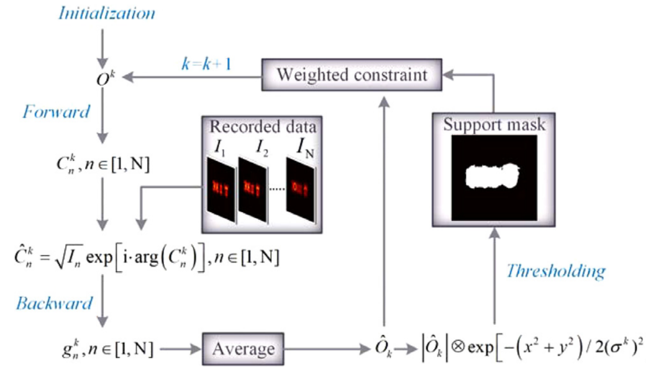

Fig. 2. The flowchart of APR method based on weighted shrink-wrap constraint (APRWS).

tude of C_n^k with the square root of the recorded intensity data $\sqrt{I_n}$ to generate synthesized complex amplitudes $\hat{C}_n^k$; (4) a set of object guesses g_n^k are obtained by a backward propagation $\mathbf{F}^{-1}[\mathbf{F}(\hat{C}_n^k)H_{Z_n}^*]$, where the superscript '*' denotes a complex conjugate operator; (5) a updated object estimation $\hat{O}^k$ is obtained by the average of all guesses; (6) the $(k+1)$th object function is assigned as: $O^{k+1} = \hat{O}^k$; (7) running circularly from step (2)–(6) until a full wave filed of object is acquired.

In the step (5) of APR method, different average operations actually affect the convergence quality. The average of all object guesses can be operated as two types:

$$\hat{O}^k = \frac{1}{\mathrm{N}}\sum_{n=1}^{\mathrm{N}} g_n^k, \tag{1}$$

$$\hat{O}^k = \left(\frac{1}{\mathrm{N}}\sum_{n=1}^{\mathrm{N}} \left|g_n^k\right|\right)\exp\left[\frac{\mathrm{i}}{\mathrm{N}}\sum_{n=1}^{\mathrm{N}} \arg\left(g_n^k\right)\right]. \tag{2}$$

Fig. 1 is given to determine which one is an optimal average operation for APR method. An inset in Fig. 1(a) is used for an object in simulation. The diffractive distances are arranged as: $Z_n = Z_0 + (n-1)d$, where Z_0 and d denote initial distance and equivalent interval. The simulated parameters are listed as: (1) the object is sampling with 400 ⋉ 400 pixels and pixel size ε is 3.1 μm; (2) $Z_0 = 20$ mm, $d = 1$ mm; (3) the wavelength is 532 nm; (4) the recording number N is 11 or 15. The mean square error (MSE) is selected as a metric for convergence. The operations of Eqs. (1) and (2) are termed as complex average and separate average for simplicity. As APR is run by 3000 iterations, the convergence curves of these two types are plotted in Fig. 1(a). The retrieved objects with 11 intensity observations are shown for separate and complex average operation in Fig. 1(b) and (c), respectively. The results with 15 recorded intensity images are Fig. 1(d) and (e). Fig. 1 indicates that complex average operation in Eq. (1) is beneficial to enhancing convergence speed for APR algorithm. Thus, complex-averaged APR method is used for following simulation and experiment. It is also noted from Fig. 1 that APR method is slowly convergent. Even if the measurement times is increased to 15, there are still 1000 iterations to output a desirable result. Hence it is necessary to seek a useful acceleration scheme for APR method.

A direct approach to speed up convergence is to add an object constraint in the object plane. In a standard APR model, $(k+1)$th object function is updated as:

$$O^{k+1} = \hat{O}^k. \tag{3}$$

As are proven in Refs. [16,17], APR method based on double feedback (APRDF) works well for a fast-converging recovery. Its $(k+1)$th object function is expressed as:

$$O^{k+1} = (1+a+b)\hat{O}^k - aO^k - bO^{k-1}, \tag{4}$$

where the indexes a and b denote feedback coefficients, and they are parameterized as 0.7 and 0.5, respectively. This weighted object constraint starts while $k > 2$.

Another acceleration approach is to impose a support constraint. This support-based strategy is originated from coherent diffraction imaging (CDI) [18–20], where the retrieved object is retained in the support region and the remaining data is decreased by a step-size attenuated term. With the use of a support constraint, APR method can be changed as:

$$O^{k+1} = (1-S)(\hat{O}^k - \beta O^k) + S\hat{O}^k, \tag{5}$$

where s is a binary support mask obtained from a shrink-wrap constraint, and it is used to outline support region. In this support mask, the value of 1 denotes the support region and the rest belongs to non-support region. The parameter $\beta = 0.8$ is regarded as an attenuated term. Shrink-wrap constraint [18] could export an adjustable support region.

With the iterative number increases, this exported support region will change from a loose size to a tight one. This adjustable support can be controlled as: (1) a matrix M is computed by the convolution of the kth object estimated function $\hat{O}^k$ and a Gaussian kernel as:

$$M = \left|\hat{O}^k\right| \otimes \exp\left[-(x^2+y^2)/2(\sigma^k)^2\right], \tag{6}$$

where the symbol ⊗ is a convolution operator and σ is initialized by 3ε, where ε is a pixel size related to an imaging sensor; (2) given a threshold η, a binary support mask S with a same size of M is selected as:

$$S = \begin{cases} 1 & M \geq \eta, \\ 0 & M < \eta, \end{cases} \tag{7}$$

where the threshold is calculated as: $\eta = \max(0.2\,\mathrm{M})$; (3) for next iteration, the size of support region is decreased by updating σ with:

$$\sigma^{k+1} = \begin{cases} \min(0.99\sigma^k,\ 1.5\varepsilon), & \mathrm{mod}(k,m) = 0, \\ \sigma^k & \text{otherwise}. \end{cases} \tag{8}$$

The symbol m is an update rate for support region. The symbol mod(k,m) takes the remainder when k is divided by m. With the iterative number increases, the object function and support region are together updated so that the convergence speed is enhanced by Eq. (5). APR method based on shrink-wrap constraint is termed as APRS algorithm in the following.

In this work, we aim to combine shrink-wrap constraint and double feedback acceleration for a better imaging effect. Here APR method based on weighted shrink-wrap constraint is termed as APRWS algorithm and its flowchart is outlined in Fig. 2. In APRWS, the update of object function is changed as:

$$O^{k+1} = S\left[(1+a+b)\hat{O}^k - aO^k - bO^{k-1}\right] + (1-S)\left(\hat{O}^k - \beta O^k\right) \tag{9}$$

where the parameters a, b, β are set as 0.7, 0.5, 0.8. The simulation in Fig. 3 is given to test the performance of our method. This simulation concludes two groups: 2 and 11 intensity observations. As iterative

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