Ptychographic Algorithm Using Dual-Tree Complex Wavelet Transform

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Abstract. Reconstructing the interesting complex image from multiple diffraction patterns is the goal of the ptychography. Previous ptychographic algorithms often suffer from low reconstruction quality under the low overlap ratios. To address this issue, we proposed a novel ptychographic phase retrieval (PR) algorithm of exploiting the sparsity of the image in dual-tree complex wavelet domain. The Fourier magnitude measurements are utilized to construct a data fidelity term, and the sparse representation model of the image over the dual-tree complex wavelet transform is utilized for the sparse induced regularization term. The data fidelity term and the proposed regularization term are combined to formulate a ptychographic PR optimization problem. Alternating direction method of multipliers (ADMM) and gradient descent algorithm are utilized for solving the corresponding optimization problem. Compared with previous algorithms, the experimental results indicate that the proposed algorithm can obtain reconstructed images with high quality even at low overlap ratios.

Introduction

Ptychography [1] which breakthroughs the resolution limit of the optics is a new kind of lens-less imaging technology. How to recover the interesting image or object accurately from the observed diffraction pattern is a challenge. Recent years, various algorithms have been proposed to address this problem. Among these algorithms, Ptychographical Iterative Engine (PIE) algorithm [2] proposed by Rodenburg and Faulkner is a popular one. Experimental results indicate that this algorithm can obtain reconstructed image with high quality via multiple diffraction patterns. Subsequently, Maiden et al. extended the PIE algorithm, and proposed the Extended Ptychographical Iterative Engine (ePIE) algorithm [3]. The ePIE algorithm can not only reconstruct the complex amplitude information of the image, but also can reconstruct the complex amplitude information of the probe by updating the probe location. Wen et al. [4] formulated the ptychographic phase retrieval problem, and exploited the alternating direction method of multipliers (ADMM) [5] technique to solve the corresponding problem.

For ptychography imaging, the overlap ratio is a main factor for the quality of the recovered image. In general, the higher the overlap ratio is, the better the image recovered by the algorithms. However, the high overlap ratio tends to cost effective area of image. To enhance the effective area of image, lower overlap ratio needs to be considered. How to recover the interest image effectively at low overlap ratios is a key problem of ptychography. To address this problem, in this paper, we exploit the inherent priors of the image for image reconstruction. Concretely, we attempt to exploit the sparsity of the image under the dual-tree complex wavelet transform (DTCWT) [6] to reconstruct the image with high quality from the observed diffraction patterns (Fourier magnitude measurements) at low overlap ratios. We propose the sparse representation regularization term of the image over the dual-tree complex wavelet transform, and fuse the data fidelity term to formulate a ptychographic phase retrieval optimization problem. The alternating direction method of multipliers (ADMM) technique is utilized to solve the formulated problem, and experimental results indicate that the proposed algorithm can obtain reconstructed images with high quality even at low overlap ratios.
Ptychographic Phase Retrieval

In the ptychography setup, an illuminating beam illuminates the different locations of image by moving the probe, and multiple diffraction patterns are recorded. The process can be described as

\[ b_i(\omega) = |F[P(r+R_i)O(r)]|, \quad i = 1, \ldots, N. \] (1)

Here, \( F \) is Fourier transform, \( P(r) \) is a probe, \( R_i \) is a translational vector, \( O(r) \) is the unknown object of interest.

Mathematically, the observed model can by described as:

\[ b_i = |FQ_i \cdot x|, \quad i = 1, \ldots, N. \] (2)

Here, \( Q_i \) represents the illumination matrix which corresponds to the \( i \) position of the probe. \( x \) is the underlying image or object.

Our ultimate goal is to reconstruct \( x \), therefore we consider to tackle the following problem [7]:

\[ \hat{x} = \arg\min_x \{ \sum_{i=1}^{N} \frac{1}{2} \|FQ_i \cdot x - b_i\|^2 \} . \] (3)

The above image reconstruction model indicates that the image we want to recover matches with the measured diffraction pattern. Since image prior information is not utilized in the above model, solving it effectively cannot obtain reconstructed images with high quality, especially at the low overlap ratio. Therefore, the prior knowledge is required to enable its accurate reconstruction. Incorporate the image regularization term into the model (3):

\[ \hat{x} = \arg\min_x \{ \sum_{i=1}^{N} \frac{1}{2} \|FQ_i \cdot x - b_i\|^2 + \lambda R(x) \} . \] (4)

where \( \lambda > 0 \) is the regularization parameter, and \( R(x) \) represents the regularization term which indicates the corresponding priors that utilized in image reconstruction.

Ptychographic Imaging Algorithm Based on Dual-tree Complex Wavelet Transform

Dual-tree complex wavelet can represent the image texture sparsely, therefore, it can effectively capture the image texture information. We exploit the sparsity of the image under the dual-tree complex wavelet transform to formulate the following optimization problem:

\[ \{\hat{m}, \hat{\varphi}\} = \arg\min_{m, \varphi} \{ \sum_{i=1}^{N} \frac{1}{2} \|FQ \cdot me^{j\varphi} - b_i\|^2 + \beta_1 \|Wm\|_1 + \beta_2 \|W\varphi\|_1 \} . \] (5)

Here, \( m \) is the underlying amplitude, \( \varphi \) is the underlying phase. \( \beta_1, \beta_2 \) are penalty parameters. \( W \) is the dual-tree complex wavelet transform.

We exploit the ADMM technique to solve the above ptychographic phase retrieval problem. We introduce a set of intermediate variables \( z_i = FQ \cdot me^{j\varphi}, \quad t = m, \quad y = \varphi \). The augmented Lagrangian function of (5) is defined as:

\[ \{\hat{z}_i, \hat{t}, \hat{\mu}, \hat{\varphi}, \hat{u}_i, \hat{z}_i, \hat{\xi}_i, \hat{\zeta}_i, \hat{\xi}_i, \hat{\zeta}_i, \hat{u}_i\} = \arg\min_{z_i, t, y, \varphi, \zeta_1, \zeta_2, u_i} \{ \sum_{i=1}^{N} \frac{1}{2} \|z_i - b_i\|^2 + \beta_1 \|Wt\|_1 + \beta_2 \|Wy\|_1 \}
+ \lambda \sum_{i=1}^{N} \|FQ \cdot me^{j\varphi} - z_i + \mu_i\|_2^2 + \lambda_2 \|m - t + \zeta_1\|_2^2 + \lambda_3 \|\varphi - y + \zeta_2\|_2^2 \} \] (6)

Here, \( \lambda, \lambda_2, \lambda_3 \) are the relaxation parameters, \( \zeta_1, \zeta_2, u_i \) are the scaled dual variables. We exploit the following steps to update the unknown variables \( z_i, t, m, y, \varphi, \zeta_1, \zeta_2, u_i \) respectively (to the \( k \) th iteration):
1) Fix the other variables, and update the variable $z_i$:

$$z_i^k = \arg \min_{z_i} \left\{ \frac{1}{2} \left\| z_i - b_i \right\|^2 + \lambda_i \sum_{j=1}^{N} \left\| \mathbf{F} \mathbf{Q} m^{k-1} e^{j\varphi_i^{k-1}} - z_i + u_i^{k-1} \right\|^2 \right\}. \quad (7)$$

To minimize the above cost function, the phase of $z_i^k$ needs to satisfy

$$\angle z_i^k = \angle (\mathbf{F} \mathbf{Q} m^{k-1} e^{j\varphi_i^{k-1}} + u_i^{k-1}).$$

Therefore, the optimization of $z_i$ can be translated into the optimization problem about $|z_i|:

$$|z_i|^k = \arg \min_{|z_i|} \left\{ \frac{1}{2} \sum_{j=1}^{N} \left| z_i \right|^2 - \left| b_i \right|^2 + \lambda_i \sum_{j=1}^{N} \left| z_i \right|^2 - \left| \mathbf{F} \mathbf{Q} m^{k-1} e^{j\varphi_i^{k-1}} + u_i^{k-1} \right|^2 \right\}. \quad (8)$$

The closed-form solution to the above problem is:

$$|z_i|^k = \frac{b_i + 2\lambda_i \left| \mathbf{F} \mathbf{Q} m^{k-1} e^{j\varphi_i^{k-1}} + u_i^{k-1} \right|}{1 + 2\lambda_i}. \quad (9)$$

Therefore, the optimal solution of $z_i$ is:

$$z_i^k = |z_i|^k e^{j\angle (\mathbf{F} \mathbf{Q} m^{k-1} e^{j\varphi_i^{k-1}} + u_i^{k-1})}. \quad (10)$$

2) Fix the other variables, and update the variable $t$:

$$t_i^k = \arg \min_{t} \left\{ \beta \left\| \mathbf{W} t \right\|_0 + \lambda_2 \left\| m^{k-1} - t + \zeta_i^{k-1} \right\|^2 \right\}. \quad (11)$$

The above problem can be solved by using the hard threshold operator [8]:

$$t_i^k = \mathbf{W}^{-1} \mathbf{T}_{\sqrt{\beta/\lambda_2}} \left[ \mathbf{W} (m^{k-1} + \zeta_i^{k-1}) \right]. \quad (12)$$

Here, $\mathbf{T}_x(x) = \begin{cases} x, & \text{abs}(x) > \tau \\ 0, & \text{otherwise} \end{cases}$ is the hard threshold operator, $\tau$ is the threshold value, $\mathbf{W}^{-1}$ is dual-tree complex wavelet inverse transform. Through a large number of experiments, the series of dual-tree complex wavelet transform is 5.

3) Fix the other variables, and update the amplitude $m$:

$$m^k = \arg \min_{m} \left\{ \sum_{i=1}^{N} \lambda_i \left\| \mathbf{F} \mathbf{Q} m e^{j\varphi_i^{k-1}} - z_i^k + u_i^{k-1} \right\|^2 + \lambda_2 \left\| m - t^k + \zeta_i^{k-1} \right\|^2 \right\}. \quad (13)$$

Let $\mathbf{E}^{k-1} = \text{Diag}(e^{j\varphi_i^{k-1}})$, (13) can be rewritten as:

$$m^k = \arg \min_{m} \left\{ \sum_{i=1}^{N} \lambda_i \left\| \mathbf{F} \mathbf{Q} \mathbf{E}^{k-1} m - z_i^k + u_i^{k-1} \right\|^2 + \lambda_2 \left\| m - t^k + \zeta_i^{k-1} \right\|^2 \right\}. \quad (14)$$

The closed-form solution to the above problem is:

$$m^k = \frac{\lambda_2 (t^k - \zeta_i^{k-1}) + \lambda_1 \sum_{i=1}^{N} \left( \mathbf{E}^{k-1} \right)^H \mathbf{Q}^H (z_i^k - u_i^{k-1})}{\lambda_2 + \lambda_1 \sum_{i=1}^{N} \left( \mathbf{E}^{k-1} \right)^H \mathbf{Q}^H \mathbf{E}^{k-1}}. \quad (15)$$

Here, $\mathbf{F}^H, \mathbf{Q}^H, (\mathbf{E}^{k-1})^H$ is the conjugate transpose of $\mathbf{F}, \mathbf{Q}, \mathbf{E}^{k-1}$ respectively.

4) Fix other variables, and update the intermediate variable $y$:
\[
y^k = \arg\min_y \{ \beta_2 \|Wy\|_0 + \lambda_3 \|y + \zeta_2^{k-1}\|_2^2 \}.
\] (16)

Using the hard threshold operator to solve the above problem, and obtain:
\[
y^k = W^{-1}^T \left( \frac{\partial}{\partial \phi} [W (\phi^{k-1} + \zeta_2^{k-1})] \right).
\] (17)

5) Fix the other variables, and update the phase \( \phi \):
\[
\phi^k = \arg\min_{\phi} \left\{ \sum_{i=1}^N \lambda_1 \|FQ \cdot m^k e^{j\phi} - z_i^k + u_i^{k-1}\|_2^2 + \lambda_3 \|\phi - y^k + \zeta_2^{k-1}\|_2^2 \right\}.
\] (18)

Denote the cost function of the above optimization problem as \( f(\phi) \), and the first-order derivative of \( \phi \) is:
\[
\nabla f(\phi) = 2\lambda_1 \{-j e^{-j\phi} (m^k)^H \sum_{i=1}^N [Q_i^H Q_i m^k e^{j\phi} - Q_i^H F^H (z_i^k - u_i^{k-1})]\} + 2\lambda_3 (\phi - y^k + \zeta_2^{k-1}).
\] (19)

Here, \((m^k)^H\) is the conjugate transpose of \(m^k\). The gradient descent algorithm is utilized to solve the optimization problem. Through a large number of experiments, the number of gradient descent is 15, set \( j = 15 \), the initial value is \( \phi^0 = \phi^{k-1} \). The gradient descent method can be expressed as:
\[
\phi^j = \phi^{j-1} - \alpha \nabla f(\phi^{j-1}),
\] where \( \alpha \) is step length factor. As a result, the optimal solution of \( \phi \) is:
\[
\phi^k = \phi^j.
\] (20)

6) Fix the other variables, and update scale dual variables \( \zeta_1, \zeta_2, u_i \):
\[
\begin{align*}
\zeta_1^k &= \zeta_1^{k-1} + \gamma (m^k - t^k) \\
\zeta_2^k &= \zeta_2^{k-1} + \gamma (\phi^j - y^k) \\
u_i^k &= u_i^{k-1} + \gamma (FQ \cdot m^k e^{j\phi^j} - z_i^k).
\end{align*}
\] (22)

The ptychographic algorithm based on the dual-tree complex wavelet transform (ADMM_DTCWT) is presented in Table 1.

<table>
<thead>
<tr>
<th>Table 1. The proposed ptychographic algorithm.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Input:</strong> the actual measurement of amplitude ( b_i, i = 1, ..., N );</td>
</tr>
<tr>
<td><strong>Initialization:</strong> ( m^0, \phi^0 ) is random value, ( \zeta_1, \zeta_2, u_i ) is 0, ( \text{iter} = 600 );</td>
</tr>
<tr>
<td><strong>for</strong> ( k = 1: \text{iter} ) <strong>do</strong></td>
</tr>
<tr>
<td>(1) According to (10), update variable ( z_i^k );</td>
</tr>
<tr>
<td>(2) According to (12), update variable ( t_i^k );</td>
</tr>
<tr>
<td>(3) According to (15), update amplitude ( m^k );</td>
</tr>
<tr>
<td>(4) According to (17), update variable ( y^k );</td>
</tr>
<tr>
<td>(5) ( \phi^0 = \phi^{k-1} );</td>
</tr>
<tr>
<td><strong>for</strong> ( j = 1:15 ) <strong>do</strong></td>
</tr>
<tr>
<td>According to (20), update phase ( \phi^j );</td>
</tr>
<tr>
<td><strong>end</strong></td>
</tr>
<tr>
<td>(6) ( \phi^k = \phi^j );</td>
</tr>
<tr>
<td>(7) According to (22), update the scale dual variables ( \zeta_1^k, \zeta_2^k, u_i^k );</td>
</tr>
<tr>
<td><strong>end</strong></td>
</tr>
<tr>
<td><strong>Output:</strong> the recovered amplitude ( m^k ), the recovered phase ( \phi^k ).</td>
</tr>
</tbody>
</table>
The Experimental Results

The standard gray images Lena and Peppers shown in Figure 1 are utilized to construct the amplitude and the phase of the original image respectively. The size of image is $512 \times 512$. The pixel value of the amplitude is $[0, 1]$, the pixel value of the phase is $[0, \pi]$. In this paper, using circular hole as probe function, radius of round hole is 80 pixels, scanning positions are four lines and four columns. We tune the overlap ratio by moving the center of circular hole in the horizontal direction and vertical direction. $\sigma \in [0, 2r]$ is the distance between the adjacent circle hole center, $r$ is the radius of round hole. The definition of the overlap ratio [9] is:

$$\delta = \frac{2r - \sigma}{2r} \times 100\%.$$  \hspace{1cm} (23)

The traditional Ptychographic phase retrieval algorithm generally chooses the overlap ratio between 50\%~80\%. To demonstrate the superiority of the proposed algorithm, this paper chooses the overlap ratio less than 50\%. The experiments have no noise and noise. No noise, the experiment chooses different overlap ratio; Noisy, adding different noise intensity under different overlap ratio. In this paper, using Peak Signal to Noise Ratio (PSNR) and Rooted Mean Square Error (RMSE) to evaluate the quality of reconstructed image, the higher PSNR, the lower RMSE, the higher quality of reconstructed image. In order to ensure the fairness, the number of iterations are 600 times, all algorithms use the random initial value, making 16 times experiments independently, and calculating the mean value of PSNR and RMSE after 16 times.

Figure 1. The standard gray images for testing in the experiments.

Table 2. The reconstructed results of amplitude and phase (No noise).

<table>
<thead>
<tr>
<th>The overlap ratio</th>
<th>Algorithm</th>
<th>Amplitude PSNR(dB)</th>
<th>Phase PSNR(dB)</th>
<th>Amplitude RMSE</th>
<th>Phase RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>40%</td>
<td>ADMM</td>
<td>18.86</td>
<td>19.84</td>
<td>0.1201</td>
<td>0.3198</td>
</tr>
<tr>
<td></td>
<td>PIE</td>
<td>34.16</td>
<td>38.58</td>
<td>0.0196</td>
<td>0.0370</td>
</tr>
<tr>
<td></td>
<td>ADMM_DTCWT</td>
<td>40.18</td>
<td>42.15</td>
<td>0.0098</td>
<td>0.0245</td>
</tr>
<tr>
<td>42.5%</td>
<td>ADMM</td>
<td>21.53</td>
<td>25.35</td>
<td>0.0838</td>
<td>0.1696</td>
</tr>
<tr>
<td></td>
<td>PIE</td>
<td>35.85</td>
<td>40.52</td>
<td>0.0161</td>
<td>0.0296</td>
</tr>
<tr>
<td></td>
<td>ADMM_DTCWT</td>
<td>41.17</td>
<td>46.71</td>
<td>0.0087</td>
<td>0.0145</td>
</tr>
</tbody>
</table>

(a) Original amplitude (b) Original phase (c) Amplitude (ADMM) (d) Phase (ADMM)
Noiseless Case

Under the noiseless case, the overlap ratios are 40% and 42.5%. The ADMM algorithm and PIE algorithm are selected as the benchmark algorithms. When the overlap ratio is 40%, parameters are: $\lambda_1=0.38$, $\lambda_2=0.31$, $\lambda_3=0.1$, $\alpha=0.4$, $\gamma=0.75$, if $k \leq 500$, $\beta_1=0.1-0.0001998k$, $\beta_2=0.004-0.00000078k$, otherwise $\beta_1=0.0001$, $\beta_2=0.0001$. When the overlap ratio is 42.5%, parameters are: $\lambda_1=0.38$, $\lambda_2=0.31$, $\lambda_3=0.001$, $\alpha=0.4$, $\gamma=0.75$, if $k \leq 500$, $\beta_1=0.2-0.0003998k$, $\beta_2=0.004-0.00000078k$, otherwise $\beta_1=0.0001$, $\beta_2=0.0001$. The recovered results are presented in Table 2. One can see from the table that the reconstructed result of the proposed algorithm is superior to other algorithms. Figure 2 shows the result at the overlap ratio 40%. From Figure 2, compared with other algorithms, one can see that ADMM algorithm cannot recover the image effectively. One can see that PIE is obviously better than results of the ADMM algorithm, outlines of amplitude and phase are relatively clear, but there are still obvious local twill. However, the proposed algorithm can reconstruct the amplitude and phase effectively. The experimental results show that the dual-tree complex wavelet transform is effective.

Table 3. The reconstructed results of amplitude and phase.

<table>
<thead>
<tr>
<th>The overlap ratio</th>
<th>Noise intensity</th>
<th>Algorithm</th>
<th>Amplitude PSNR(dB)</th>
<th>Phase PSNR(dB)</th>
<th>Amplitude RMSE</th>
<th>Phase RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>40%</td>
<td>5%</td>
<td>ADMM</td>
<td>17.27</td>
<td>19.69</td>
<td>0.1368</td>
<td>0.3254</td>
</tr>
<tr>
<td></td>
<td></td>
<td>PIE</td>
<td>33.27</td>
<td>37.72</td>
<td>0.0217</td>
<td>0.0408</td>
</tr>
<tr>
<td></td>
<td></td>
<td>ADMM_DTCWT</td>
<td><strong>37.03</strong></td>
<td><strong>39.54</strong></td>
<td><strong>0.0141</strong></td>
<td><strong>0.0331</strong></td>
</tr>
<tr>
<td></td>
<td>10%</td>
<td>ADMM</td>
<td>15.92</td>
<td>17.92</td>
<td>0.1598</td>
<td>0.3972</td>
</tr>
<tr>
<td></td>
<td></td>
<td>PIE</td>
<td>33.13</td>
<td>37.54</td>
<td>0.0220</td>
<td>0.0417</td>
</tr>
<tr>
<td></td>
<td></td>
<td>ADMM_DTCWT</td>
<td><strong>35.45</strong></td>
<td><strong>36.26</strong></td>
<td><strong>0.0169</strong></td>
<td><strong>0.0483</strong></td>
</tr>
<tr>
<td>42.5%</td>
<td>5%</td>
<td>ADMM</td>
<td>18.13</td>
<td>20.76</td>
<td>0.1240</td>
<td>0.2876</td>
</tr>
<tr>
<td></td>
<td></td>
<td>PIE</td>
<td>35.69</td>
<td>40.30</td>
<td>0.0164</td>
<td>0.0303</td>
</tr>
<tr>
<td></td>
<td></td>
<td>ADMM_DTCWT</td>
<td><strong>38.21</strong></td>
<td><strong>40.80</strong></td>
<td><strong>0.0123</strong></td>
<td><strong>0.0286</strong></td>
</tr>
<tr>
<td></td>
<td>10%</td>
<td>ADMM</td>
<td>17.57</td>
<td>20.43</td>
<td>0.1322</td>
<td>0.2989</td>
</tr>
<tr>
<td></td>
<td></td>
<td>PIE</td>
<td>35.27</td>
<td><strong>39.86</strong></td>
<td>0.0171</td>
<td><strong>0.0316</strong></td>
</tr>
<tr>
<td></td>
<td></td>
<td>ADMM_DTCWT</td>
<td><strong>35.96</strong></td>
<td><strong>37.77</strong></td>
<td><strong>0.0160</strong></td>
<td><strong>0.0402</strong></td>
</tr>
</tbody>
</table>

(a) Original amplitude  (b) Original phase  (c) Amplitude (ADMM)  (d) Phase (ADMM)
Noise Case
The noise intensity 5% and 10% (refer to reference [10]) of the Gaussian noise are added onto the true diffraction patterns, and we utilized the noise diffraction patterns for image reconstruction. When the overlap ratio is 40%, the parameters are: $\lambda_1=0.38$, $\lambda_2=0.31$, $\lambda_3=0.1$, $\alpha=0.4$, $\gamma=0.75$; When noise intensity is 5%, if $k \leq 500$, $\beta_1=0.1-0.00019988k$, $\beta_2=0.004-0.0000078k$, otherwise $\beta_1=0.0006$, $\beta_2=0.0001$. When the noise intensity is 10%, if $k \leq 500$, $\beta_1=0.1-0.00019988k$, $\beta_2=0.004-0.0000068k$, otherwise $\beta_1=0.0006$, $\beta_2=0.0006$. When the overlap ratio is 42.5%, the parameters are: $\lambda_1=0.38$, $\lambda_2=0.31$, $\lambda_3=0.01$, $\alpha=0.4$, $\gamma=0.75$. When noise intensity is 5%, if $k \leq 500$, $\beta_1=0.1-0.0001998k$, $\beta_2=0.001-0.0000018k$, otherwise $\beta_1=0.0001$, $\beta_2=0.0001$. When noise intensity is 5%, if $k \leq 500$, $\beta_1=0.1-0.00019988k$, $\beta_2=0.01-0.0000188k$, otherwise $\beta_1=0.0006$, $\beta_2=0.0006$. One can see from Table 3, the PSNR of the reconstructed amplitude is higher than the benchmark algorithms, and the RMSE of reconstructed amplitude obtained by the proposed algorithm is lower than the benchmark algorithms. Figure 3 shows the results at noise intensity 5% case. We can see from Figure 3, ADMM algorithm cannot recover the outline of amplitude and phase. The amplitude and phase are reconstruct by PIE algorithm have obvious twill. The proposed algorithm reconstructs outline and detail clearly. The experimental shows that the proposed algorithm is robust to noise.

Conclusion
In this work, we have presented a ptychographic imaging algorithm. The dual-tree complex wavelet which can represent the image texture information effectively is utilized to construct the spare representation regularization term. The ptychographic phase retrieval optimization problem of utilizing the DDWT is formulated, and the ADMM technique is utilized to solve it effectively. The experimental results validate that the proposed algorithm can reconstruct the amplitude and phase effectively under the low overlap ratio, compared with PIE algorithm and ADMM algorithm. Moreover, the proposed algorithm is robust to noise.

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