

Phase retrieval imaging for nano-scale images using MATLAB

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Abstract— The advent of ‘Nano’ has encroached almost all the trending application areas. Nano imaging is such area where the conventional imaging systems are replaced by nano imaging to get the better results about the images. In regard the paper treats 3 phase-retrieval methods like Error-reduction algorithm (ER), Hybrid input-output algorithm (HIO) and Shrinkwrap algorithm along with error. In previous these algorithms were derived for conventional images the same is extended for nano scale images and analyzed over different parameters. The simulation results in MATLAB summarizes the parameters which are crucial for the betterment of the resulting images.

Keywords—ER, HIO, Phase Retrieval

I. INTRODUCTION

Images at nanoscale can be obtained from imaging devices like Scanning Electron Microscope (SEM), Transmission Electron Microscope (TEM), Atomic Force Microscope (AFM) etc. The level of energy produced by the interaction of electrons on specimen surface is measured to obtain SEM and TEM images [1]. These nanoscale images help us to understand important properties of nanostructures and hence numerous image processing techniques are being developed for analyzing these images [1-3]. Particularly in the bio-medical field imaging like in X-ray Computed Tomography(CT) has 2 method of image acquisition 1. Attenuation based imaging 2. Phase contrast imaging. The first has lack of sensitivity and specificity and images mainly depends on attenuation level which is reduced gradually. Hence the latter gains the popularity because

- its least absorption or similar absorption in multi-material objects
- phase-shift for low-Z elements hikes sensitivity in threefold
- phase-contrast is high even at low absorption level leads to lowering the dose

In phase-contrast imaging, the Fresnel diffraction intensity pattern is measured in accordance to the phase shift in the beam induced by the object. The relationship between the

induced phase shift and the intensity is recorded at a distance of D [sample-to-detector distance]. However, phase information is not directly recorded in the measured intensity of diffracted wave field but it is to be extracted from the diffraction pattern. Hence phase shift is proportional to a projection real part of the complex refractive index distribution in the object [4] This can be achieved by:

1. Phase retrieval: phase shift induced by the object is extracted for each projection angle
2. Reconstruction: Using a standard reconstruction algorithm is applied on phase projections, to 3D reconstruction of the refractive decrement index δr .

Section I contains the introduction of nano images and imaging techniques, Section II contain the related work of nano images and phase-retrieval method, Section III contain the some algorithms related to Phase retrieval in imaging techniques, Section IV contains MATLAB implementation of different algorithms and finally Section V describes results and discussion.

II. RELATED WORK

There are plenty of methods for phase retrieval problem like

1. Transport of Intensity Equation (TIE) [5-10] which is based on the use of a series of image measurements obtained at different short propagation distances (usually two distances D).
2. Above can be refined by Gerchberg-Saxton-Fienup algorithms (GSF) [11,12]
3. Contrast Transfer Function (CTF) [13-15] can give good results even with weak absorption and slowly varying phase

In all these methods there is a linear relationship between the phase and the intensity and hence considered to be approximations of the direct problem of phase contrast image formation.

4. Mixed approach [16]
5. a given ratio of the imaginary to the real part of the refractive index has been developed [17] for a homogeneous object and also can be extended for multi-object [18].

The limitations are due to the linearity other methods can refine taking non-linearity of phase problem.

III. ITERATIVE PHASE RETRIEVAL ALGORITHMS

These are usually based on the Gerchberg-Saxton (GS) algorithm which considers intensity at object and image planes [11]. The two-phase distributions are reconstructed by propagating the complex-valued wavefront is propagated back and forth between the object plane and the diffraction pattern (detector) plane and replacing amplitudes at each iteration. But diffraction pattern is the only one intensity measurement is available and hence some a priori information about the object distribution is known. The amplitude of the updated wavefront in the detector plane is the square root of the measured intensity and object distribution in the object plane by known values like zeros according to oversampling condition. This constraint along with object distribution must be real and positive behaves like object "support". The goal is to recover the object complex-valued distribution $f(x,y)$ from the measured intensity distribution $I(v,w)=|F(v,w)|^2$. The reconstruction is depicted in the figure.1.

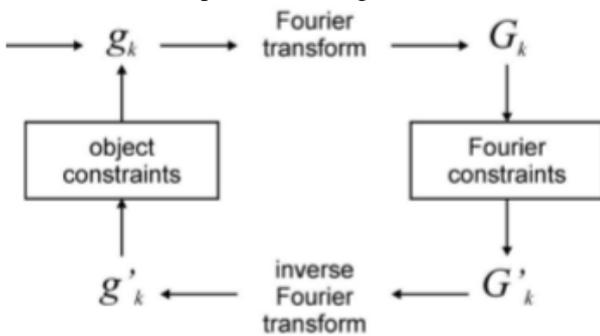


Figure.1: Block diagram to shows reconstruction

A. Error-reduction algorithm (ER):

The steps of the error-reduction (ER) algorithm at k-th iteration [12]:

1. $G_k(v,w) = |G_k(v,w)| \exp[i\phi_k(v,w)] = F[g_k(x,y)]$
2. $G'_k(v,w) = |F(v,w)| \exp[i\phi_k(v,w)]$
3. $g'_k(x,y) = |g'_k(v,w)| \exp[i\theta'_k(v,w)] = F^{-1}[G'_k(x,y)]$
4. $g_{k+1}(x,y) = \begin{cases} g'_k(x,y), & \text{if } (x,y) \in \gamma \\ 0, & \text{if } (x,y) \notin \gamma \end{cases}$

Where, $g_k, \theta'_k, G'_k, \phi_k \rightarrow$ Estimates of f, η, F and Ψ

$F, F^{-1} \rightarrow$ Fourier and inverse Fourier Transform.

$\gamma \rightarrow$ set of points at which $g'_k(x,y)$ is positive real - valued

The estimate of the object distribution $g_k(x,y)$ ($k = 1$ for the first iteration) can be measured by

- 1) A complex-valued far-field distribution is obtained by combining the square root of the measured intensity as the amplitude and a distribution of random numbers with phase $-\pi$ to π . The inverse FT of the obtained distribution gives $g(x,y)$
- 2) A random complex-valued distribution multiplied with a known support gives $g(x,y)$

k-th iteration error, $E_{fk} = \left\{ \frac{N^{-2} \sum_{v,w} [|G_k(v,w)| - |F(v,w)|]^2}{\sum_{v,w} [|F(v,w)|]^2} \right\}^{0.5} \leq$ error at the previous iteration [12].

B. Hybrid input-output algorithm (HIO)

This [12] is obtained by modifying ER algorithm in the constraints of object domain. At k-th iteration the changes are

$$g_{k+1}(x,y) = \begin{cases} g'_k(x,y), & \text{if } (x,y) \in \gamma \\ g_k(x,y) - \beta g'_k(x,y), & \text{if } (x,y) \notin \gamma \end{cases}$$

where $\beta \rightarrow$ constant.

$$\text{Error Function, } E_{fk} = \left\{ \frac{\sum_{(x,y) \in \gamma} [|g'_k(x,y)|]^2}{\sum_{(x,y) \in \gamma} [|g'_k(x,y)|]^2} \right\}^{0.5}$$

C. Shrinkwrap algorithm:

This [19] is a modification of the HIO algorithm, where the object support in step (iv) is re-adjusted during the iterative reconstruction at each 20-th iteration. Eventually, the object support approaches the exact shape of the object distribution, thus providing a "tight support".

IV. IMPLEMENTATION:

A. SIMULATION OF DIFFRACTION PATTERN:

- In the diffraction pattern of the image is taken. Only the red plane of the selected image is taken for the simulation of the diffracting pattern. The Value of each pixel is taken as
- Pixel value = $\frac{\text{Pixel value} - \text{Min. pixel value}}{\text{Max. pixel value} - \text{min. Pixel value}}$
- The obtained image is subject to 2-D Fourier transform and displayed in log scale to get the diffraction pattern of the image. This is used in different algorithms.

B. MODIFIED ERROR-REDUCTION ITERATIVE PHASE RETRIEVAL ALGORITHM

Step 1: Reading diffraction pattern

Step 2: Creating initial complex-valued field distribution at the detector plane by multiplying the exponential complex to the square root of diffraction pattern.

Step 3: Getting initial object distribution by taking the inverse Fourier transform of result in step -2

Step-4: Creating support in object domain by setting the threshold to $\frac{1}{4}$ th resolution of the image

Step 5: Iterative loop consisting

- replacing updated amplitude for measured amplitude
- getting updated object distribution
- object and Threshold constraint

Step 6: With successive iterations, HIO has a tendency for the values at a given pixel to oscillate somewhat with increasing iteration number. The conjecture was that the oscillations had to do with the fact that the input image at the next iteration is a discontinuous function of the output image.

C. MODIFIED HYBRID INPUT-OUTPUT ITERATIVE PHASE RETRIEVAL ALGORITHM

Steps are similar to that of ER algorithm except the changes in the formula as described earlier.

D. MODIFIED SHRINKWRAP ITERATIVE PHASE RETRIEVAL ALGORITHM

Algorithm evaluates autocorrelation of the object at first. This real space map, obtained by Fourier transforming the diffraction pattern, displays all "interatomic" vectors, with peaks for all vectors between isolated objects, shifted to a common origin. It contains many more peaks than the object, and, even for an acentric object, possesses a center of inversion symmetry. Since the object must fit within the autocorrelation function, the first estimate of the support is a mask obtained from this function using a contour at the 4% intensity level. Both the correct object density and its centro-symmetric inversion fit within this initially centric mask, however inversion symmetry is progressively lost as the algorithm converges. Apply the changes in HIO algorithm with feedback parameter $\beta = 0.9$ and the real space support given by the calculated mask. We obtain the part of the diffraction pattern covered by a central beam stop from the transform of the current estimate of the object. Low frequency components are treated as free parameters. Every 20 iterations we convolve the reconstructed image (the absolute value of the reconstructed wavefield) with a Gaussian of width σ (FWHM = 2.3548σ) to find the new support mask. The mask is then obtained by applying a threshold at 20% of its maximum. The width σ is set to 3 pixels in the first iteration, and reduced by 1% every 20 iterations down to a minimum of 1.5 pixels.

E. ALIGNMENT OF RECONSTRUCTED SAMPLE DISTRIBUTIONS WITH FLIPPING

- Reading reconstructed object
- Creating reference image
- Alignment of sequence of images
- Calculating cross-correlation

- Calculating flipping
- calculating cross-correlation2
- selecting whether to flip or not to flip the current image

V. RESULTS AND DISCUSSION

A. Input:

A nano scale image is taken as the input shown in Figure.2

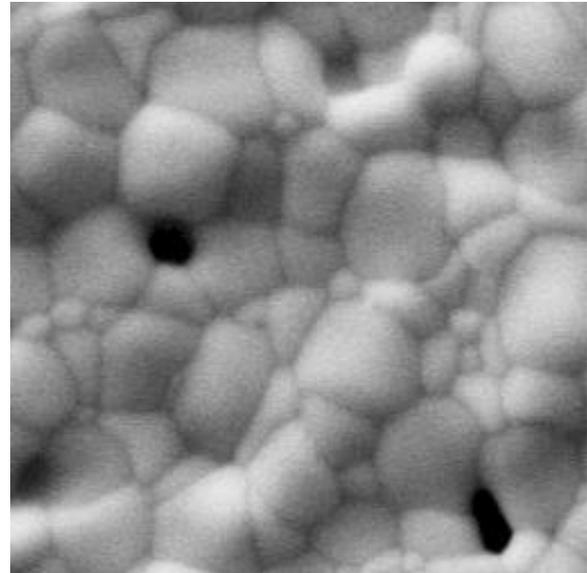


Figure2. Input Nano Scale image.

The following are considered

- parameter in HIO algorithm, $\beta = 0.9$
- threshold in the object domain = 1
- number of iterations = 200
- number of pixels = 256
- $p = 0.01$

B. SIMULATION OF DIFFRACTION PATTERN:

Figure 3 shows the resultant image of diffraction pattern for the selected image in the Figure 2.

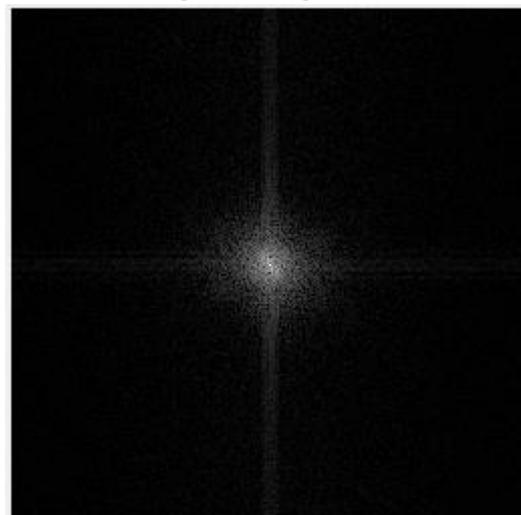


Figure 3: Diffraction Pattern

Figure 4 shows the resultant image of ER algorithm for the diffraction pattern in the Figure 3.

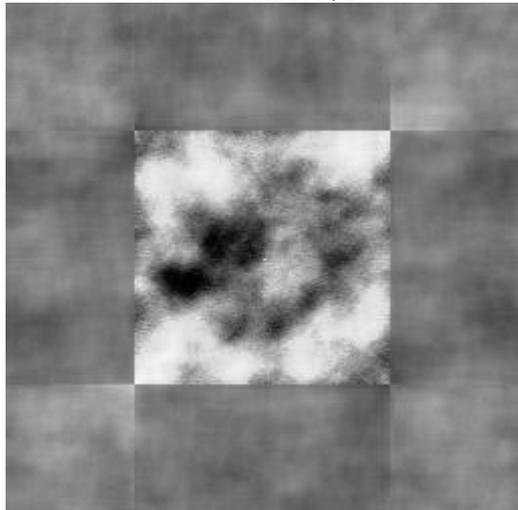


Figure 4: Output of ER algorithm

Figure 5 shows the resultant image of CHIO algorithm for the diffraction pattern in the Figure 3.

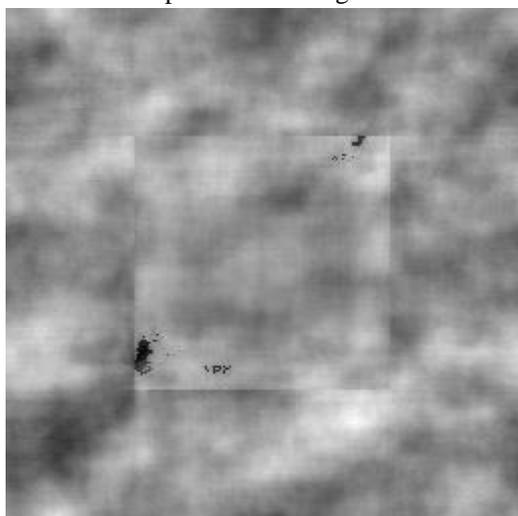


Figure 5: Output of HIO algorithm

Figure 6 shows the resultant image of Shrinkwrap algorithm for the diffraction pattern in the Figure 3.

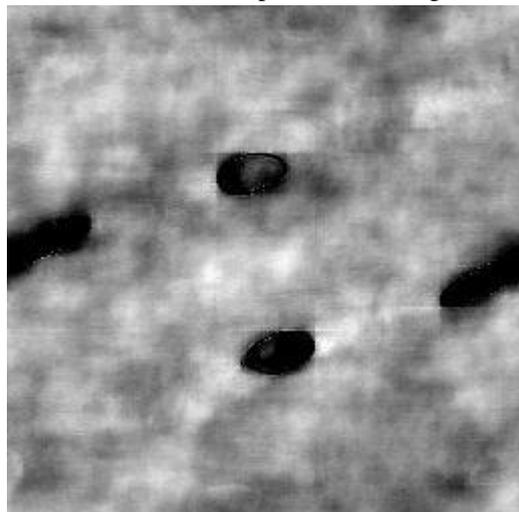


Figure 6: Output of SW algorithm

Figure 7 shows the resultant image of alignment of reconstructed sample distributions with flipping of ER

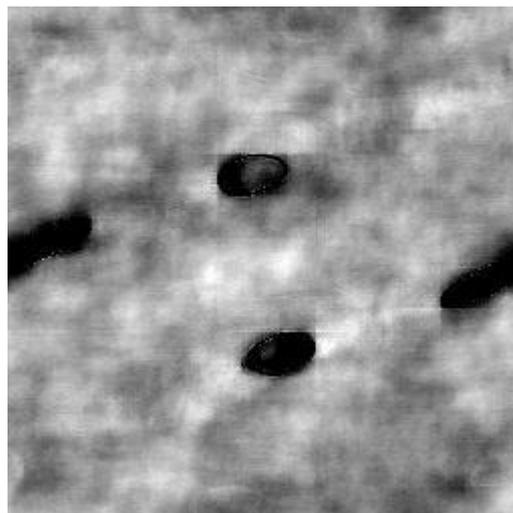


Figure 4: Output of Alignment

Errors after the 200 iterations are:

- ER algorithm: 0.7829
- HIO algorithm: 1.6655
- Shrinkwrap algorithm: 1.0000e+10

VI. CONCLUSION

- The paper lists the vital parameters for successful iterative phase retrieval.
- It gives a hint that the experimental parameters must satisfy oversampling condition and its oversampling factor is a less crucial factor.
- For better reconstruction, a high intensity dynamic range and absence of distortions in the acquired diffraction pattern are essential
- Faulty pixels of the detecting system or missing central spot are can be recovered during the iterative phase retrieval.
- All algorithms can be adjusted and optimized for particular experimental data.
- The results show better results with Shrinkwrap algorithm with minimal error in reconstruction.
- The paper shows that the algorithms is suitable for Nano scale images.

VII. REFERENCES

- [1] Eralci M, Therézio, Maria L. Vega, Roberto M. Faria and Alexandre Marletta, Statistical Analysis in Homopolymeric Surfaces, www.intechopen.com.
- [2] Eraldo Ribeiro, Mubarak Shah, Computer Vision for Nanoscale imaging, Machine Vision and Applications(2006) 17:147-162.
- [3] Toshihiko Ogura and Chikara Sato, An Automatic Particle Pickup Method Using a Neural Network Applicable to Low-Contrast Electron Micrographs, Journal of Structural Biology 136,227–238 (2001).
- [4] Cloetens, P., Ludwig, W., Baruchel, J., Guigay, J.-P., PernotRejmánková, P., Salomé-Pateyron, M., Schlenker, M.,

- Buffiere, J.-Y., Maire, E., and Peix, G. (1999). Hard X-ray phase imaging using simple propagation of a coherent synchrotron radiation beam. *J. Phys. D: Appl. Phys.*, 32:A145–A151.
- [5] Nugent, K. A., Gureyev, T., Cookson, D., Paganin, D., and Barnea, Z. (1996). Quantitative phase imaging using hard X-rays. *Phys. Rev. Lett.*, 77:2961–2964.
- [6] Barty, A., Nugent, K. A., Paganin, D., and Roberts, A. (1998). Quantitative optical phase microscopy. *Opt. Lett.*, 23:817–819.
- [7] Beleggia, M., Schofield, M. A., Volkov, V. V., and Zhu, Y. (2004). On the transport of intensity technique for phase retrieval. *Ultramicroscopy*, 102:37–49.
- [8] Gureyev, T. E., Raven, C., Snigirev, A., Snigireva, I., and Wilkins, S. W. (1999). Hard X-ray quantitative non-interferometric phase-contrast microscopy. *J. Phys. D: Appl. Phys.*, 32:563–567.
- [9] Paganin, D. (2006). *Coherent X-ray optics*. Oxford University Press, New York, USA.
- [10] Turner, L., Dhal, B., Hayes, J., Mancuso, A., Nugent, K., Paterson, D., Scholten, R., Tran, C., and Peele, A. (2004). X-ray phase imaging: demonstration of extended conditions for homogeneous objects. *Opt. Express*, 12:2960–2965.
- [11] Gureyev, T. (2003). Composite techniques for phase retrieval in the Fresnel region. *Opt. Commun.*, 220:49–58.
- [12] Fienup, J. (1982). Phase retrieval algorithms: a comparison. *Appl. Opt.*, 21:2758–2769.
- [13] Guigay, J. (1977). Fourier transform analysis of Fresnel diffraction patterns in in-line holograms. *Optik*, 46:12–125.
- [14] Cloetens, P., Barrett, R., Baruchel, J., Guigay, J. P., and Schlenker, M. (1996). Phase objects in synchrotron radiation hard X-ray imaging. *J. Phys. D*, 29:133–146.
- [15] Zabler, S., Cloetens, P., Guigay, J.-P., Baruchel, J., and Schlenker, M. (2005). Optimization of phase contrast imaging using hard X-rays. *Rev. Sci. Instrum.*, 76:1–7.
- [16] Langer, M., Cloetens, P., and Peyrin, F. (2010). Regularization of phase retrieval with phase attenuation duality prior for 3D holotomography. *IEEE Trans. Image Process.*, 19:2425–2436.
- [17] Paganin, D., Mayo, S. C., Gureyev, T., Miller, P. R., and Wilkins, S. W. (2002). Simultaneous phase and amplitude extraction from a single defocused image of a homogeneous object. *J. Microsc.*, 206:33–40.
- [18] Beltran, M. A., Paganin, D. M., Uesugi, K., and Kitchen, M. J. (2010). 2D and 3D X-ray phase retrieval of multi-material objects using a single defocus distance. *Opt. Express*, 18:6423–6436.
- [19] S. Marchesini et al., "X-ray image reconstruction from a diffraction pattern alone," *Phys. Rev. B* 68, 140101 (2003).