



Solving Fourier Phase Retrieval with a Reference Image as a Sequence of Linear Inverse Problems

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Fourier Phase Retrieval Problem

- □ Recovering a signal from its Fourier amplitude measurements
- □ Equivalent to recovering a signal from its autocorrelation
- Nonlinear and nonconvex optimization problem
- □ Robust recovery
 - Good initialization
 - □ Prior information about the sparsity or support of the target signal

Applications:

X-ray crystallography [1], diffraction imaging [2], ptychography [3]



Phase Retrieval Methods

- Classical phase retrieval methods
 - Error reduction and alternating minimization algorithms
 - (Fienup HIO [4] and Gerchberg-Saxton [5])
 - Exploit prior knowledge about the **non-negativity** and **support** of the target object in the scene
- □ Convex relaxation methods
 - PhaseLift [6] and PhaseCut [7]
 - Lifting the problem to a high-dimensional space
 - □ Theoretical recovery guarantees only exist for **random measurements**
- □ Directly solving the non-convex optimization problem
 - □ Wirtinger Flow [8], Amplitude Flow [9] and their variants
 - □ Require **careful initialization** to avoid local minima

^[4] J. R. Fienup, "Reconstruction of an object from the modulus of its Fourier transform," Opt. Lett., Jul 1978

^[5] R. W. Gerchberg and W. Saxton, "A practical algorithm for the determination of phase from image and diffraction plane pictures," Optik, 1972

^[6] E. J. Candes, et. al, "Phaselift: Exact and stable signal recovery from magnitude measurements via convex programming," CPAM, 2012.

^[7] I. Waldspurger, A. Aspremont, and S. Mallat, "Phase recovery, maxcut and complex semidefinite programming," Mathematical Programming, Feb 2015

^[8] E. J. Candes, X. Li, and M. Soltanolkotabi, "Phase retrieval via wirtinger flow: Theory and algorithms," IEEE Transactions on Information Theory, April 2015.

^[9] G. Wang, et. al "Solving systems of random quadratic equations via truncated amplitude flow," IEEE Trans on Information Theory, Feb 2018



Fourier Phase Retrieval with Known Reference

Linear method

- □ Presence of a reference signal makes the signal recovery problem linear [10, 11, 13]
- □ The existing methods only work if the support of the reference and target signals are sufficiently separated [10,11, 12, 13]

Nonlinear method

- □ No separation condition is needed
- The known signal with any arbitrary size and shapes can be imposed as an image domain constraint
- □ The method is a nonlinear iterative method based on Alternating Minimization and Gradient Descent [14]

^[10] D. A. Barmherzig, J. Sun, E. J. Candes, T. J. Lane, and P Li, "Holographic phase retrieval and optimal reference design," Inverse Problems, 2019

^[11] M. Sicairos and J. R. Fienup, "Holography with extended reference by autocorrelation linear differential operation," Opt. Express, Dec 2007.

^[12] M. Sicairos and J. R. Fienup, "Direct image reconstruction from a Fourier intensity pattern using heraldo.," Optics letters, 2008

^[13] Z. Yuan and H. Wang, "Phase retrieval with back-ground information," Inverse Problems, 2019

^[14] F. Arab and M. S. Asif, "Fourier Phase Retrieval with Arbitrary Reference Signal," ICASSP 2020





Fourier Phase Retrieval with Known Reference

Motivation



Proposed method





Problem Formulation

Fourier phase retrieval can be written as the following nonlinear deconvolution problem

$$\min_{\mathbf{X}} \|\mathbf{R} - \mathbf{X} \star \mathbf{X}\|_2^2,$$

- □ X is the unknown image
- \square R is the known 2D observed autocorrelation measurements of X
- \Box * denotes 2D cross-correlation operator





Problem Formulation

- □ We can vectorize the matrices and write the autocorrelation equation as $vec(\mathbf{R}) = C_{\mathbf{X}}vec(\mathbf{X}),$
- □ Where C_X is the Toeplitz matrix of X, vec(R) and vec(X) are vectorized versions of R and X. We can also rewrite is as

$$\begin{bmatrix} \mathbf{r}_1 \\ \mathbf{r}_2 \\ \mathbf{r}_3 \\ \vdots \\ \mathbf{r}_i \end{bmatrix} = \begin{bmatrix} C_{\mathbf{x}_q} & \mathbf{0} & \mathbf{0} & \dots & \mathbf{0} \\ C_{\mathbf{x}_{q-1}} & C_{\mathbf{x}_q} & \mathbf{0} & \dots & \mathbf{0} \\ C_{\mathbf{x}_{q-2}} & C_{\mathbf{x}_{q-1}} & C_{\mathbf{x}_q} & \dots & \mathbf{0} \\ \vdots & \vdots & \vdots & \dots & \vdots \\ C_{\mathbf{x}_1} & C_{\mathbf{x}_2} & C_{\mathbf{x}_3} & \dots & C_{\mathbf{x}_q} \end{bmatrix} \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \\ \mathbf{x}_3 \\ \vdots \\ \mathbf{x}_q \end{bmatrix},$$



Proposed Method: Sequential Deconvolution Method

□ Reference as known columns on both sides

Step 1:
$$\mathbf{r}_2 = C_{\mathbf{x}_1}^l \mathbf{x}_{q-1} + C_{\mathbf{x}_q} \mathbf{x}_2 = \begin{bmatrix} C_{\mathbf{x}_1}^l & C_{\mathbf{x}_q} \end{bmatrix} \begin{bmatrix} \mathbf{x}_{q-1} \\ \mathbf{x}_2 \end{bmatrix},$$

Step 2: $\mathbf{r}_3 - \hat{C}_{\mathbf{x}_{q-1}} \hat{\mathbf{x}}_2 \approx \begin{bmatrix} C_{\mathbf{x}_1}^l & C_{\mathbf{x}_q} \end{bmatrix} \begin{bmatrix} \mathbf{x}_{q-2} \\ \mathbf{x}_3 \end{bmatrix}.$
Step k: $\mathbf{r}_{k+1} - \sum_{i=1}^{i=k-1} \hat{C}_{\mathbf{x}_{q-k+i}} \hat{\mathbf{x}}_{i+1} \approx \begin{bmatrix} C_{\mathbf{x}_1}^l & C_{\mathbf{x}_q} \end{bmatrix} \begin{bmatrix} \mathbf{x}_{q-k} \\ \mathbf{x}_{k+1} \end{bmatrix}$

□ Reference as known columns on one side

- □ First estimate few columns from the other sides using linear inverse problem
- □ Then, everything is similar to the first scenario: estimate two columns at a time



Proposed Method

Algorithm 1 Proposed sequential recovery method

Inputs: $\mathbf{r}_2, ..., \mathbf{r}_{K+1}, \mathbf{x}_1, \mathbf{x}_q$, and K K: depends on the number of columns in the image for k = 1, ..., K do

$$\begin{bmatrix} \hat{\mathbf{x}}_{q-k} \\ \hat{\mathbf{x}}_{k+1} \end{bmatrix} = \begin{bmatrix} C_{\mathbf{x}_1}^l & C_{\mathbf{x}_q} \end{bmatrix}^{-1} \left(\mathbf{r}_{k+1} - \sum_{i=1}^{i=k-1} \hat{C}_{\mathbf{x}_{q-k+i}} \hat{\mathbf{x}}_{i+1} \right)$$

end for Output: $\hat{\mathbf{x}}_2, ..., \hat{\mathbf{x}}_{q-1}$

We estimate two columns at each iteration



Stability and Recovery Conditions

Stability of the algorithm at each step

- □ It depends only on the condition of matrix $H = \begin{bmatrix} C_{\mathbf{x}_1}^l & C_{\mathbf{x}_q} \end{bmatrix}$
- □ For special references such as two pinholes at two sides of the image, H is full rank, for other references, we should make sure that it is full column rank
- □ The Toeplitz matrices of the first and last columns need to have incoherent columns

□ Stability of the overall system

- The overall system, as shown in the system matrix, depends on the pixel values in the unknown image
- This condition is much harder to evaluate

Stability of the proposed sequential method

- Presence of measurement noise and finite precision of multiplications and additions in the crosscorrelation terms causes an accumulation of error
- □ If the system is not well-conditioned, it will cause instability



Experiments

□ Motivation

- □ The main motivation comes from **"looking around the corner problem"**
 - □ The reflectivity of the target objects in the scene that are hidden from the view is estimated
 - We are given the autocorrelation of the entire scene (objects within the direct line of sight and those hidden around the corner)
 - In our experiments, some parts of the scene such as the background or border around the object are known apriori
- □ Another motivation is related to the **Fourier phase retrieval for a video sequence**
 - We may perfectly know parts of the scene that are static (e.g., background) and can be incorporated as side information





Simulation Results

□ Sequential recovery with a known border

- □ First scenario: reference border is two pinholes on both sides
- Dataset
 - □ Sample natural images
- Other parameters
 - $\Box \quad Border \ width = 8 \ pixels$

Different amounts of Gaussian measurement noise





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Simulation Results

□ Sequential recovery with a known border

Second scenario: a border with variable width around the images is known

Dataset

□ Frames from three sequences of KTH dataset

Other parameters

- □ Border width = variable
- No noise

Known area = ratio of the pixels in the known border to the total number of pixels







Simulation Results

□ Sequential recovery with a known patch

- **Dataset**
 - Sample natural images
- Other parameters
 - □ A pinhole reference is added to the right side of the image
 - Different amounts of separation (h)



Separation between unknown object and known pinhole





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Simulation Results

Comparison to the existing methods

- □ Linear method is not applicable in this scenario
- **Dataset**

□ Sample natural images and video frames from KTH dataset

Alternating minimization without side information

Nonlinear method

Proposed sequential method





Summary

- We proposed a sequential method to solve Fourier phase retrieval problem with a known reference
- □ No constraints on the separation between known reference and target image
- □ We solved the problem as a sequence of deconvolutions
- Simulation results showed that our method can reliably recover images from Fourier amplitude measurements under different settings for reference and measurement noise levels

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