

# A Local Analysis of Block Coordinate Descent for Gaussian Phase Retrieval

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## 1. Introduction

- Converge of ADMM is guaranteed for convex functions
- Also works well on nonconvex functions empirically but not well-understood
- We analyze phase retrieval as a model nonconvex function to understand local convergence

## 2. Phase Retrieval and ADMM

The Gaussian Phase Retrieval (GPR) problem: Recover  $x \in \mathbb{R}^n$  from the measurements  $y_k = |\mathbf{a}_k^* x|$ ,  $k = 1, \dots, m$  ( $\mathbf{a}_k$ 's are i.i.d Gaussian vectors). A biconvex least-squares formulation:

$$\begin{aligned} \text{minimize}_{\mathbf{z}, \mathbf{w} \in \mathbb{R}^n} \quad & f(\mathbf{z}, \mathbf{w}) \doteq \frac{1}{4m} \sum_{k=1}^m \left( y_k^2 - \mathbf{a}_k^T \mathbf{z} \mathbf{a}_k^T \mathbf{w} \right)^2 \\ \text{subject to} \quad & \mathbf{z} = \mathbf{w}. \end{aligned} \quad (2.1)$$

ADMM updates for Eq. (2.1):

$$\begin{aligned} \mathbf{z}^{(k+1)} &= \arg \min_{\mathbf{z}} \mathcal{L}(\mathbf{z}, \mathbf{w}^{(k)}, \boldsymbol{\lambda}^{(k)}), \\ \mathbf{w}^{(k+1)} &= \arg \min_{\mathbf{w}} \mathcal{L}(\mathbf{z}^{(k+1)}, \mathbf{w}, \boldsymbol{\lambda}^{(k)}), \\ \boldsymbol{\lambda}^{(k+1)} &= \boldsymbol{\lambda}^{(k)} + \rho (\mathbf{z}^{(k+1)} - \mathbf{w}^{(k+1)}), \end{aligned} \quad (2.2)$$

where  $\rho > 0$  and  $\mathcal{L}$  is the augmented Lagrangian:

$$\mathcal{L}(\mathbf{z}, \mathbf{w}, \boldsymbol{\lambda}) \doteq f(\mathbf{z}, \mathbf{w}) + \langle \boldsymbol{\lambda}, \mathbf{z} - \mathbf{w} \rangle + \frac{\rho}{2} \|\mathbf{z} - \mathbf{w}\|^2. \quad (2.3)$$

## 3. A natural reduction to block coordinate descent

**Lemma 3.1.** A triple  $(\mathbf{z}, \mathbf{w}, \boldsymbol{\lambda})$  is a critical point of  $\mathcal{L}(\mathbf{z}, \mathbf{w}, \boldsymbol{\lambda})$  if and only if

$$\partial_{\mathbf{z}} f = \partial_{\mathbf{w}} f = \mathbf{0}, \quad \mathbf{z} = \mathbf{w}, \quad \boldsymbol{\lambda} = \mathbf{0}. \quad (3.1)$$

Motivates fixing  $\boldsymbol{\lambda} = \mathbf{0}$  so that ADMM becomes block coordinate descent (BCD):

$$\begin{aligned} \mathbf{z}^{(k+1)} &= \arg \min_{\mathbf{z}} f(\mathbf{z}, \mathbf{w}^{(k)}) + \frac{\rho}{2} \|\mathbf{z} - \mathbf{w}^{(k)}\|^2, \\ \mathbf{w}^{(k+1)} &= \arg \min_{\mathbf{w}} f(\mathbf{z}^{(k+1)}, \mathbf{w}) + \frac{\rho}{2} \|\mathbf{z}^{(k+1)} - \mathbf{w}\|^2. \end{aligned} \quad (3.2)$$

## 4. Linear Convergence

Consider the expected objective function:

$$g(\mathbf{z}, \mathbf{w}) \doteq \mathbb{E} [f(\mathbf{z}, \mathbf{w})] + \frac{\rho}{2} \|\mathbf{z} - \mathbf{w}\|^2 \quad (4.1)$$

$$= \frac{3}{2} \|\mathbf{x}\|^4 + (\mathbf{w}^T \mathbf{z})^2 + \frac{1}{2} \|\mathbf{z}\|^2 \|\mathbf{w}\|^2 - 2\mathbf{x}^T \mathbf{z} \mathbf{x}^T \mathbf{w} - \|\mathbf{x}\|^2 \mathbf{w}^T \mathbf{z} + \frac{\rho}{2} \|\mathbf{z} - \mathbf{w}\|^2. \quad (4.2)$$

Using a spectral initialization (i.e., see [1]), we may assume  $(\mathbf{z}^{(0)}, \mathbf{w}^{(0)})$  lies within the set:

$$N_{\mathbf{x}} \doteq \left\{ (\mathbf{z}, \mathbf{w}) : \|\mathbf{z} - \mathbf{x}\| \leq \frac{1}{8} \|\mathbf{x}\| \text{ and } \|\mathbf{w} - \mathbf{x}\| \leq \frac{1}{8} \|\mathbf{x}\| \right\}. \quad (4.3)$$

**Lemma 4.1 (Local strong convexity).** Suppose  $\rho \geq \|\mathbf{x}\|^2$ . For all  $(\mathbf{z}, \mathbf{w}) \in N_{\mathbf{x}}$ ,

$$\nabla^2 g(\mathbf{z}, \mathbf{w}) \succeq \frac{1}{3} \|\mathbf{x}\|^2 \mathbf{I}. \quad (4.4)$$

**Lemma 4.2 (No-escape).** Suppose  $\rho \geq \frac{27}{8} \|\mathbf{x}\|^2$ . The BCD iterate sequence  $\{(\mathbf{z}^{(k)}, \mathbf{w}^{(k)})\}$  stays in  $N_{\mathbf{x}}$ .

**Lemma 4.3 (Locally block Lipschitz).**  $g(\mathbf{z}, \mathbf{w})$  is block Lipschitz on  $N_{\mathbf{x}}$ , i.e., for all  $(\mathbf{z}, \mathbf{w}) \in N_{\mathbf{x}}$  and all  $\mathbf{h}_z, \mathbf{h}_w \in \mathbb{R}^n$ ,

$$\|\nabla_{\mathbf{z}} g(\mathbf{z} + \mathbf{h}_z, \mathbf{w}) - \nabla_{\mathbf{z}} g(\mathbf{z}, \mathbf{w})\| \leq (4\|\mathbf{x}\|^2 + \rho) \|\mathbf{h}_z\|, \quad (4.5)$$

$$\|\nabla_{\mathbf{w}} g(\mathbf{z}, \mathbf{w} + \mathbf{h}_w) - \nabla_{\mathbf{w}} g(\mathbf{z}, \mathbf{w})\| \leq (4\|\mathbf{x}\|^2 + \rho) \|\mathbf{h}_w\|. \quad (4.6)$$

With local convexity in place, we establish a linear convergence rate:

**Theorem 4.4.** Suppose  $\rho \geq \frac{27}{8} \|\mathbf{x}\|^2$  and  $(\mathbf{z}^{(0)}, \mathbf{w}^{(0)}) \in N_{\mathbf{x}}$ . Then, the BCD iterate sequence converges linearly to the point  $(\mathbf{x}, \mathbf{x})$  with the rate given by:

$$\|(\mathbf{z}^{(k)}, \mathbf{w}^{(k)}) - (\mathbf{x}, \mathbf{x})\| \leq \left( 1 - \frac{\|\mathbf{x}\|^2}{12\|\mathbf{x}\|^2 + 3\rho} \right)^{k/2} \sqrt{\frac{6}{\|\mathbf{x}\|} [g(\mathbf{z}^{(0)}, \mathbf{w}^{(0)}) - g(\mathbf{x}, \mathbf{x})]}. \quad (4.7)$$

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## References

[1] Mondelli, M. and Montanari, A. Fundamental Limits of Weak Recovery with Applications to Phase Retrieval. *arXiv preprint*, arXiv:1708.05932.