

Non-Convex Recovery from Phaseless Low-Resolution Blind Deconvolution Measurements using Noisy Masked Patterns

Samuel Pinilla[†], Kumar Vijay Mishra[‡], and Brian Sadler[‡] [†]Faculty of Information Technology and Communication Sciences, Tampere University

[‡]United States CCDC Army Research Laboratory, Adelphi, MD 20783 USA

Here, we provide some mathematical proofs that support the theoretical analysis of the paper.

APPENDIX A: PROOF OF THEOREM 1

Due to homogeneity in (10), it suffices to work with the case where $\|\mathbf{x}\| = 1$. Instrumental in proving Theorem 2 is the following result. Additionally, in order to model the effect of the low-pass filter \mathcal{G} in Algorithm 1 consider the diagonal matrix $\mathbf{L}_{\mathcal{G}} \in \mathbb{R}_+^{n \times n}$ whose entries satisfy $0 < (\mathbf{L}_{\mathcal{G}})_{i,i} < 1$. This inequality constraint is assumed without loss of generality to model the contribution of the frequencies in the Fourier domain.

Lemma 1. Consider the noisy data $|\mathbf{a}_i^H \mathbf{x}|^2 + (\omega)_i = |\mathbf{a}_i^H \mathbf{F}^H \boldsymbol{\alpha}|^2 + (\omega)_i$, with $\boldsymbol{\alpha} = \mathbf{F}\mathbf{x}$ such that $\|\boldsymbol{\omega}\|_{\infty} \leq c\|\mathbf{x}\|_{\infty}$ for some $c > 0$. For any unit vector $\boldsymbol{\alpha} \in \mathbb{C}^n$, there exists a vector $\mathbf{u} \in \mathbb{C}^n$ with $\mathbf{u}^H \boldsymbol{\alpha} = 0$ and $\|\mathbf{u}\| = 1$, such that

$$\frac{1}{2} \|\boldsymbol{\alpha} \boldsymbol{\alpha}^H - \hat{\boldsymbol{\theta}} \hat{\boldsymbol{\theta}}^H\|_F^2 \leq \frac{\|\mathbf{S} \mathbf{L}_{\mathcal{G}} \mathbf{u}\|_2^2}{\|\mathbf{S} \mathbf{L}_{\mathcal{G}} \boldsymbol{\alpha}\|_2^2} + \mathcal{O}(\|\boldsymbol{\omega}\|_{\infty})^1, \quad (19)$$

where $\mathbf{S} = \left[\frac{\mathbf{b}_1}{\|\mathbf{b}_1\|_2}, \dots, \frac{\mathbf{b}_J}{\|\mathbf{b}_J\|_2} \right]^H$ for $i \in \mathcal{I}_0$, with $J = \text{card}(\mathcal{I}_0)$ is the cardinality of \mathcal{I}_0 . Recall that the vectors \mathbf{b}_i are the rows of the matrix $\mathbf{B} = \mathbf{A}\mathbf{F}$, and $\hat{\boldsymbol{\theta}}$ is the solution of (9).

Proof. Notice that

$$\begin{aligned} \frac{1}{2} \|\boldsymbol{\alpha} \boldsymbol{\alpha}^H - \hat{\boldsymbol{\theta}} \hat{\boldsymbol{\theta}}^H\|_F^2 &= \frac{1}{2} \|\boldsymbol{\alpha}\|_2^4 + \frac{1}{2} \|\hat{\boldsymbol{\theta}}\|_2^4 - |\boldsymbol{\alpha}^H \hat{\boldsymbol{\theta}}|^2 \\ &= 1 - |\boldsymbol{\alpha}^H \hat{\boldsymbol{\theta}}|^2 = 1 - \cos^2(\beta) \\ &= \sin^2(\beta), \end{aligned} \quad (20)$$

where $\beta \in [0, \pi/2]$ is the angle between the spaces spanned by $\hat{\boldsymbol{\theta}}$ and $\boldsymbol{\alpha}$. Then one can write

$$\boldsymbol{\alpha} = \cos(\beta) \hat{\boldsymbol{\theta}} + \sin(\beta) \hat{\boldsymbol{\theta}}^{\perp}, \quad (21)$$

where $\hat{\boldsymbol{\theta}}^{\perp} \in \mathbb{C}^n$ is a unit vector orthogonal to $\hat{\boldsymbol{\theta}}$ and the real part of its inner product with $\boldsymbol{\alpha}$ is non-negative. Then from (21) we have that

$$\boldsymbol{\alpha}^{\perp} = -\sin(\beta) \hat{\boldsymbol{\theta}} + \cos(\beta) \hat{\boldsymbol{\theta}}^{\perp}, \quad (22)$$

¹The notation $\varphi(w) = \mathcal{O}(g(w))$ means there exists a numerical constant $c > 0$ such that $\varphi(w) \leq cg(w)$.

in which $\boldsymbol{\alpha}^{\perp} \in \mathbb{C}^n$ is a unit vector orthogonal to $\boldsymbol{\alpha}$. Thus, considering (21), (22) and appealing to Lemma 1 in [1], we obtain that

$$\frac{1}{2} \|\boldsymbol{\alpha} \boldsymbol{\alpha}^H - \hat{\boldsymbol{\theta}} \hat{\boldsymbol{\theta}}^H\|_F^2 \leq \frac{\|\mathbf{S} \mathbf{L}_{\mathcal{G}} \boldsymbol{\alpha}^{\perp}\|_2^2}{\|\mathbf{S} \mathbf{L}_{\mathcal{G}} \boldsymbol{\alpha}\|_2^2} + \mathcal{O}(\|\boldsymbol{\omega}\|_{\infty}). \quad (23)$$

Then, taking $\mathbf{u} = \boldsymbol{\alpha}^{\perp}$ the result holds. \square

We now turn to prove Theorem 2. The first step consists in upper-bounding the term on the right hand-side of (23). Specifically, its numerator term will be upper bounded, and the denominator term lower bounded, which are summarized in the following lemmas.

Lemma 2. Assume that $\sum_{\ell=1}^L \mathbf{D}_{\ell}^H \mathbf{D}_{\ell} = r\mathbf{I}$ for some $r > 0$ with $L \geq c_0 n$ for some sufficiently large constant $c_0 > 0$. In the setup of Lemma 1, if $\text{card}(\mathcal{I}_0) \geq C_1 n$, then the next

$$\|\mathbf{S} \mathbf{L}_{\mathcal{G}} \mathbf{u}\|_2^2 \leq \gamma_1 r (1 + \delta - \zeta) \text{card}(\mathcal{I}_0) \quad (24)$$

holds for $\delta, \zeta, \gamma_1 \in (0, 1)$ with probability at least $1 - 2e^{-Cn}$ provided that L is sufficiently large.

Proof. In order to proof this lemma observe that

$$\mathbf{E} = \sum_{i=1}^{nL} \frac{\mathbf{b}_i \mathbf{b}_i^H}{\|\mathbf{b}_i\|_2^2} = \sum_{\ell=1}^L \frac{\mathbf{D}_{\ell}^H \mathbf{D}_{\ell}}{\|\mathbf{D}_{\ell}\|_F^2} \approx r\mathbf{I},$$

since the Fourier transform matrix \mathbf{F} is an orthogonal matrix i.e $\mathbf{F}^H \mathbf{F} = \mathbf{F} \mathbf{F}^H = \mathbf{I}$. Then, from standard concentration inequality on the sum of random positive semi-definite matrices with sub-Gaussian rows [2], it can be obtained that

$$(1 - \delta) \leq \sigma_{\min} \left(\frac{1}{r} \mathbf{E} \right) \leq \sigma_{\max} \left(\frac{1}{r} \mathbf{E} \right) \leq (1 + \delta), \quad (25)$$

with probability at least $1 - 2e^{-Cn}$ as long as L is sufficiently large, for some constant $\delta \in (0, 1)$ and $C > 0$, where $\sigma_{\max}(\cdot)$ and $\sigma_{\min}(\cdot)$ denote the largest and smallest singular value, respectively. Given the fact that \mathbf{S} is a sub-matrix of \mathbf{E} , from (25) we get

$$\begin{aligned} \sigma_{\max} \left(\frac{1}{r \text{card}(\mathcal{I}_0)} \mathbf{S} \mathbf{L}_{\mathcal{G}} \right) &\leq \left(\sigma_{\max} \left(\frac{1}{r \text{card}(\mathcal{I}_0)} \mathbf{E} \right) - \zeta \right) \gamma_1 \\ &\leq (1 + \delta - \zeta) \gamma_1, \end{aligned} \quad (26)$$

for some constants $\zeta, \delta \in (0, 1)$, where $\gamma_1 = \sigma_{\max}(\mathbf{L}_G) < 1$. Thus, from (26) we have that

$$\|\mathbf{S}\mathbf{u}\|_2^2 = \|\mathbf{u}^H \mathbf{S}^H \mathbf{S} \mathbf{u}\| \leq \gamma_1 r(1 + \delta - \zeta) \text{card}(\mathcal{I}_0), \quad (27)$$

holds with probability at least $1 - 2e^{-Cn}$, provided that L is sufficiently large. Considering the fact that $\alpha^\perp = \mathbf{u}$, then we have that

$$\|\mathbf{S}\mathbf{L}_G \alpha^\perp\|_2^2 \leq \gamma_1 r(1 + \delta - \zeta) \text{card}(\mathcal{I}_0), \quad (28)$$

with high probability. Thus, the result holds. \square

Lemma 3. In the setup of Lemma 1, the following holds with probability at least $1 - 2e^{-Cn}$

$$\|\mathbf{S}\mathbf{L}_G \alpha\|_2^2 \geq \gamma_2 r(1 - \delta) \text{card}(\mathcal{I}_0), \quad (29)$$

with $\delta, \gamma_2 \in (0, 1)$ provided that L is sufficiently large.

Proof. Notice that the left side term in (29) can be seen as

$$\|\mathbf{S}\mathbf{L}_G \alpha\|_2^2 = \sum_{i \in \mathcal{I}_0} \frac{|\mathbf{b}_i^H \mathbf{L}_G \alpha|^2}{\|\mathbf{L}_G \mathbf{b}_i\|_2^2}. \quad (30)$$

Given the fact that \mathbf{S} is a sub-matrix of \mathbf{E} , from (25) we get

$$\begin{aligned} \sigma_{\min} \left(\frac{1}{r \text{card}(\mathcal{I}_0)} \mathbf{S}\mathbf{L}_G \right) &\geq \sigma_{\min} \left(\frac{1}{r \text{card}(\mathcal{I}_0)} \mathbf{E} \right) \gamma_2 \\ &\geq (1 - \delta) \gamma_2, \end{aligned} \quad (31)$$

for some constant $\delta \in (0, 1)$, and $\gamma_2 = \sigma_{\min}(\mathbf{L}_G) < 1$ with probability at least $1 - 2e^{-Cn}$ as long as L is sufficiently large, for some constant $C > 0$. Thus, from (31) it can be concluded that

$$\sum_{i \in \mathcal{I}_0} \frac{|\mathbf{b}_i^H \mathbf{L}_G \alpha|^2}{\|\mathbf{L}_G \mathbf{b}_i\|_2^2} \geq \gamma_2 r(1 - \delta) \text{card}(\mathcal{I}_0), \quad (32)$$

with probability at least $1 - 2e^{-Cn}$ as long as L is sufficiently large. Thus, from (32) we have that

$$\|\mathbf{S}\mathbf{L}_G \alpha\|_2^2 \geq \gamma_2 r(1 - \delta) \text{card}(\mathcal{I}_0), \quad (33)$$

holds with probability at least $1 - 2e^{-Cn}$, provided that L is sufficiently large. Therefore, from (33) the result holds. \square

Hence, putting together (20) and (33) it can be concluded that

$$\frac{\|\mathbf{S}\mathbf{L}_G \mathbf{u}\|_2^2}{\|\mathbf{S}\mathbf{L}_G \alpha\|_2^2} \leq \left(\frac{1 + \delta - \zeta}{1 - \delta} \right) \frac{\gamma_1}{\gamma_2} \triangleq \kappa_G < 1, \quad (34)$$

by taking $\delta < \zeta \frac{\gamma_2}{2\gamma_1}$. Thus, putting together (19) and (34) it can be obtained that

$$\sin^2(\beta) = 1 - \cos^2(\beta) \leq \kappa_G. \quad (35)$$

On the other hand, notice that

$$\begin{aligned} \text{dist}^2(\hat{\mathbf{z}}, \mathbf{x}) &\leq \|\mathbf{x}\|_2^2 + \|\hat{\mathbf{z}}\|_2^2 - 2|\mathbf{x}^H \hat{\mathbf{z}}| \\ &= \|\alpha\|_2^2 + \|\hat{\theta}\|_2^2 - |\alpha^H \hat{\theta}| \\ &= \|\alpha\|_2^2 + \|\hat{\theta}\|_2^2 - 2\cos(\beta) \\ &\leq \underbrace{2(1 - \sqrt{1 - \kappa_G})}_{\delta_G} + \mathcal{O}(\|\omega\|_\infty), \end{aligned} \quad (36)$$

where the first equality comes from the fact that $\mathbf{F}\mathbf{x} = \alpha$, and \mathbf{F} is an orthogonal matrix. Then, combining (35) and (36) we finally conclude that

$$\text{dist}^2(\hat{\mathbf{z}}, \mathbf{x}) < \delta_G + \mathcal{O}(\|\omega\|_\infty). \quad (37)$$

Thus, in (37) the result holds.

Analysis of the proof

Observe that (36) establishes the effect of the low-pass filter \mathcal{G} to approximate \mathbf{x} . Additionally, notice that $\frac{\gamma_1}{\gamma_2}$ is the condition number of \mathbf{L}_G . From this observation we can compare the performance between two different low-pass filters to solve (9). In fact, a filter \mathcal{G}_1 is able to better approximate the complex signal \mathbf{x} compared to \mathcal{G}_2 if the condition number of $\mathbf{L}_{\mathcal{G}_1}$ is smaller than $\mathbf{L}_{\mathcal{G}_2}$.

On the other hand, performing an analog procedure to proof Lemmas 1, 2 and 3 assuming that the matrix \mathbf{L}_G contains zeros in its diagonal, that is, $(\mathbf{L}_G)_{i,i} = 0$ for several $i \in \{1, \dots, n\}$, we obtain the accuracy of solving (7) to approximate \mathbf{x} . Therefore, from the previous analysis we have that a matrix $\mathbf{L}_{\mathcal{G}_1}$ containing zeros in its diagonal will have a poorer performance compared to a matrix $\mathbf{L}_{\mathcal{G}_2}$ that does not contain zeros in its diagonal, to approximate \mathbf{x} , because the rank of $\mathbf{L}_{\mathcal{G}_1}$ will be smaller than $\mathbf{L}_{\mathcal{G}_2}$. Thus, it is theoretically established that solving (9) using Algorithm 1 will return a closer approximation of \mathbf{x} compared to a solution obtained by solving (7).

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