

Eventual linear convergence of the Douglas-Rachford iteration for basis pursuit

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Abstract

We provide a simple analysis of the Douglas-Rachford splitting algorithm in the context of ℓ^1 minimization with linear constraints, and quantify the asymptotic linear convergence rate in terms of principal angles between relevant vector spaces. In the compressed sensing setting, we show how to bound this rate in terms of the restricted isometry constant. More general iterative schemes obtained by ℓ^2 -regularization and over-relaxation including the dual split Bregman method [27] are also treated, which answers the question how to choose the relaxation and soft-thresholding parameters to accelerate the asymptotic convergence rate. We make no attempt at characterizing the transient regime preceding the onset of linear convergence.

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Keywords: basis pursuit; Douglas-Rachford; generalized Douglas-Rachford; Peaceman-Rachford; relaxation parameter; asymptotic linear convergence rate

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1 Introduction

1.1 Setup

In this paper we consider certain splitting algorithms for basis pursuit [7], the constrained optimization problem

$$\min \|x\|_1 \quad \text{s.t.} \quad Ax = b. \quad (1.1)$$

Throughout this paper we consider $A \in \mathbb{R}^{m \times n}$ with $m \leq n$, and we assume that A has full row rank. We also assume that the solution x^* of (1.1) is unique.

In particular, we treat splitting algorithms that naturally arise in the scope of minimization problems of the form

$$\min_x f(x) + g(x),$$

where f and g are convex, lower semi-continuous (but not otherwise smooth), and have simple resolvents of their subdifferentials

$$J_{\gamma F} = (I + \gamma F)^{-1}, \quad J_{\gamma G} = (I + \gamma G)^{-1},$$

where $F = \partial f(x)$ and $G = \partial g(x)$ are the respective subdifferentials of f and g at x . In those terms, x is a minimizer if and only if $0 \in F(x) + G(x)$. Resolvents are also often called proximal operators, as they obey $J_{\gamma F}(x) = \arg \min_z \gamma f(z) + \frac{1}{2}\|z - x\|^2$. In the case of basis pursuit, it is well known that

- $f(x) = \|x\|_1$ and $g(x) = \iota_{\{x: Ax=b\}}$, the indicator function equal to zero when $Ax = b$ and $+\infty$ otherwise;
- $J_{\gamma F}$ is soft-thresholding (shrinkage) by an amount γ ,

$$J_{\gamma F}(x)_i = S_\gamma(x)_i = \text{sgn}(x_i) \max\{|x_i| - \gamma, 0\};$$

- $J_{\gamma G}$ is projection onto the set $Ax = b$, namely

$$J_{\gamma G}(x) = P(x) = x + A^+(b - Ax),$$

with $A^+ = A^T(AA^T)^{-1}$ denoting the pseudo inverse.

The simplest splitting algorithm based on the resolvents is

$$x^{k+1} = J_{\gamma F} J_{\gamma G} x^k.$$

This iteration is successful in the special case when f and g are both indicators of convex sets, but does not otherwise generally enjoy good convergence properties. Instead, one is led to consider reflection operators $R_{\gamma F} = 2J_{\gamma F} - I$, $R_{\gamma G} = 2J_{\gamma G} - I$, and write the *Douglas-Rachford splitting* [25, 10]

$$\begin{cases} y^{k+1} = \frac{1}{2}(R_{\gamma F} R_{\gamma G} + I)y^k = J_{\gamma F} \circ (2J_{\gamma G} - I)y^k + (I - J_{\gamma G})y^k, \\ x^{k+1} = J_{\gamma G} y^{k+1}, \end{cases} \quad (1.2)$$

where I is the identity. The operator $T_\gamma = \frac{1}{2}(R_{\gamma F}R_{\gamma G} + I)$ is *firmly non-expansive* regardless of $\gamma > 0$ [25]. Thus y^k converges to one of its fixed points y^* . Moreover, $x^* = J_{\gamma G}(y^*)$ is one solution to $0 \in F(x) + G(x)$.

For general convex functions $f(x)$ and $g(x)$, the sublinear convergence rate $\mathcal{O}(1/k)$ of the algorithm (1.2) was proven for averages of iterates in [6, 19]. The firm non-expansiveness also implies $\|y^k - y^{k-1}\|^2 \leq \frac{1}{k}\|y^0 - y^*\|^2$, see Appendix A. Convergence questions for the Douglas-Rachford splitting were recently studied in the context of projections onto possibly nonconvex sets [1, 22] with potential applications to phase retrieval [2].

In the case of basis pursuit, we note that the Douglas-Rachford (DR) iteration takes the form

$$\begin{cases} y^{k+1} = S_\gamma(2x^k - y^k) + y^k - x^k, \\ x^{k+1} = y^{k+1} + A^+(b - Ay^{k+1}). \end{cases} \quad (1.3)$$

1.2 Main result

In practice, (1.3) often settles into a regime of linear convergence. See Figure 1.1 for an illustration of a typical error curve where the matrix A is a 3×40 random matrix and x^* has three nonzero components. Notice that the error $\|y^k - y^*\|$ is monotonically decreasing since the operator T_γ is non-expansive. The same cannot be said of $\|x^k - x^*\|$.

In this example, the regime of linear convergence was reached quickly for the y^k . That may not in general be the case, particularly if AA^T is ill-conditioned. Below, we provide the characterization of the error decay rate in the linear regime. To express the result, we need the following notations.

Assume that the unique solution x^* of (1.1) has r zero components. Let e_i ($i = 1, \dots, n$) be the standard basis in \mathbb{R}^n . Denote the basis vectors corresponding to zero components in x^* as e_j ($j = i_1, \dots, i_r$). Let B be the $r \times n$ selector of the zero components of x^* , i.e., $B = [e_{i_1}, \dots, e_{i_r}]^T$. Let $\mathcal{N}(A) = \{x : Ax = 0\}$ denote the nullspace of A and $\mathcal{R}(A^T) = \{x : x = A^T z, z \in \mathbb{R}^m\}$ denote the range of A^T .

Then, for the numerical example discussed earlier, the slope of $\log \|y^k - y^*\|$ as a function of k is $\log(\cos \theta_1)$ for large k , where θ_1 is the first principal angle between $\mathcal{N}(A)$ and $\mathcal{N}(B)$. See Definition 2.3 in Section 2.3 for principal angles between subspaces.

Our main result is that the rate of decay of the error is indeed $\cos \theta_1$ for a large class of situations that we call *standard*, in the sense of the following definition.

Definition 1.1. Consider a basis pursuit problem (b, A) with solution x^* . Consider y^0 an initial value for the Douglas-Rachford iteration, and $y^* = \lim_{k \rightarrow \infty} T_\gamma^k y^0$.

Consider the preimage of the soft thresholding of all vectors with the same signs as x^* :

$$\mathcal{Q} = \{S_\gamma^{-1}(x) : \text{sgn}(x) = \text{sgn}(x^*)\} = Q_1 \otimes Q_2 \otimes \dots \otimes Q_n,$$

where

$$Q_j = \begin{cases} (\gamma, +\infty), & \text{if } x_j^* > 0 \\ (-\infty, -\gamma), & \text{if } x_j^* < 0 \\ [-\gamma, \gamma], & \text{otherwise} \end{cases}.$$

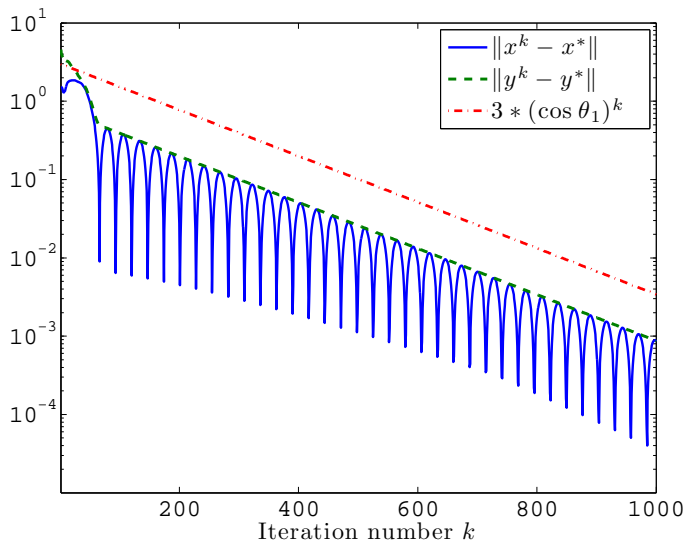


Figure 1.1: A typical error curve for Douglas-Rachford

We call $(b, A; y^0)$ a standard problem for the Douglas-Rachford iteration if $R(y^*)$ belongs to the interior of \mathcal{Q} , where R is the reflection operator defined earlier. In that case, we also say that the fixed point y^* of T_γ is an interior fixed point. Otherwise, we say that $(b, A; y^0)$ is nonstandard for the Douglas-Rachford iteration, and that y^* is a boundary fixed point.

Theorem 1.2. Consider $(b, A; y^0)$ a standard problem for the Douglas-Rachford iteration, in the sense of the previous definition. Then the Douglas-Rachford iterates y^k obey

$$\|y^k - y^*\| \leq C (\cos \theta_1)^k, \quad \forall k \geq K,$$

where C and K may depend on b , A and y^0 , and θ_1 is the leading principal angle between $\mathcal{N}(A)$ and $\mathcal{N}(B)$.

The auxiliary variable y^k in (1.3) converges linearly for sufficiently large k , thus x^k is also bounded by a linearly convergent sequence since $\|x^k - x^*\| = \|P(y^k) - P(y^*)\| = \|P(y^k - y^*)\| \leq \|y^k - y^*\|$.

Intuitively, convergence enters the linear regime when the support of the iterates essentially matches that of x^* . By essentially, we mean that there is some technical consideration (embodied in our definition of a “standard problem”) that this match of supports is not a fluke and will continue to hold for all iterates from k and on. When this linear regime is reached, our analysis in the standard case hinges on the simple fact that $T_\gamma(y^k) - y^*$ is a linear transformation on $y^k - y^*$ with an eigenvalue of maximal modulus equal to $\cos \theta_1$.

In the nonstandard case (y^* being a boundary fixed point), we furthermore show that the rate of convergence for y^k is *generically* of the form $\cos \bar{\theta}_1$, where $0 < \bar{\theta}_1 \leq \theta_1$ is the leading principal angle between $\mathcal{N}(A)$ and $\mathcal{N}(\bar{B})$, with \bar{B} a submatrix of B depending on y^* . Nongeneric cases are not a priori excluded by our analysis, but have not been observed in our numerical tests. See Section 2.5 for a discussion of the different types of nonstandard cases.

1.3 Regularized basis pursuit

In practice, if θ_1 is very close to zero, linear convergence with rate $\cos \theta_1$ might be very slow. The following regularized problem is often used to accelerate convergence,

$$\min_x \left\{ \|x\|_1 + \frac{1}{2\alpha} \|x\|^2 : Ax = b \right\}. \quad (1.4)$$

It is proven in [28] that there exists a α_∞ such that the solution of (1.4) with $\alpha \geq \alpha_\infty$ is the solution of (1.1). See [23] for more discussion of α_∞ . For the rest of this paper, we assume α is taken large enough so that $\alpha \geq \alpha_\infty$.

For all the discussion regarding ℓ^2 -regularized basis pursuit, it is convenient to make the technical assumption that $\theta_1 \leq \frac{\pi}{4}$. Notice that regularization is probably unwarranted in the event $\theta_1 > \pi/4$, since $\cos \theta_1$ would be a very decent linear convergence rate.

In particular, the Douglas-Rachford splitting (1.2) with $f(x) = \|x\|_1 + \frac{1}{2\alpha} \|x\|^2$ and $g(x) = \iota_{\{x: Ax=b\}}$ is equivalent to the dual split Bregman method for basis pursuit [27], which will be discussed in Section 4.3.

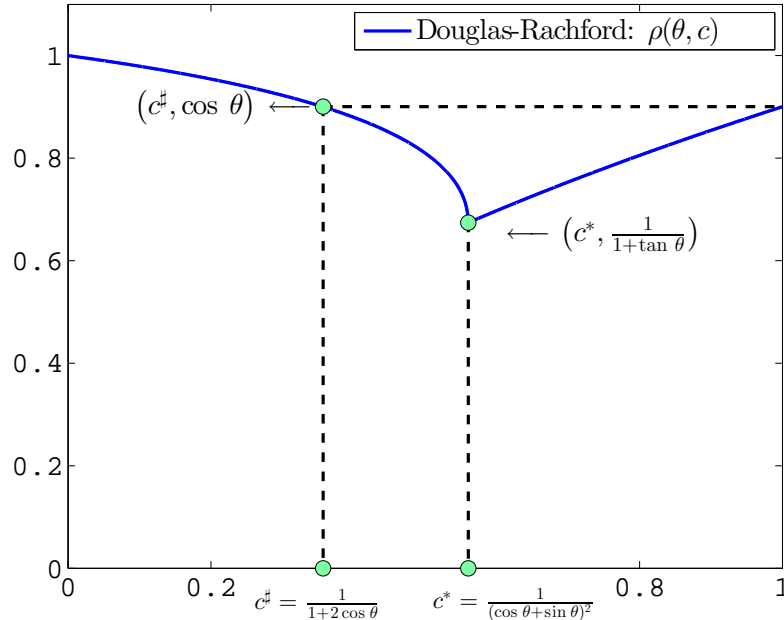


Figure 1.2: An illustration of the rate of linear convergence for Douglas-Rachford splitting on ℓ^2 -regularized basis pursuit: $\rho(\theta, c)$ for a fixed θ . The vertical axis is $\rho(\theta, c)$ and the horizontal axis is $c = \frac{\alpha}{\alpha + \gamma}$. The case $\alpha = +\infty$ (unregularized DR) is at $c = 1, \rho = \cos \theta$.

With the same assumptions and notations as in Theorem 1.2, assuming $\theta_1 \leq \frac{\pi}{4}$, for the Douglas-Rachford splitting (1.2) on (1.4), we have $\|y^k - y^*\| \leq C \rho(\theta_1, c)^k$ where $c = \frac{\alpha}{\alpha + \gamma}$ and

$$\rho(\theta, c) = \begin{cases} \sqrt{c} \cos \theta, & \text{if } c \geq \frac{1}{(\cos \theta + \sin \theta)^2} \\ \frac{1}{2} \left(c \cos(2\theta) + 1 + \sqrt{\cos^2(2\theta)c^2 - 2c + 1} \right) & \text{if } c \leq \frac{1}{(\cos \theta + \sin \theta)^2} \end{cases}.$$

Let $c^* = \frac{1}{(\cos \theta_1 + \sin \theta_1)^2}$ which is equal to $\arg \min_c \rho(\theta_1, c)$. Let $c^\sharp = \frac{1}{1+2\cos \theta_1}$ which is a solution to $\rho(\theta_1, c) = \cos \theta_1$. See Figure 1.2. Then for any $c \in (c^\sharp, 1)$, we have $\rho(\theta_1, c) < \cos \theta_1$. The asymptotic convergence rate of (1.2) on (1.4) is faster than (1.3) if $\frac{\alpha}{\alpha+\gamma} \in (c^\sharp, 1)$. The best achievable asymptotic convergence rate is $\rho(\theta_1, c^*) = \sqrt{c^*} \cos \theta_1 = \frac{\cos \theta_1}{\cos \theta_1 + \sin \theta_1} = \frac{1}{1+\tan \theta_1}$ when $\frac{\alpha}{\alpha+\gamma} = c^*$.

1.4 Generalized Douglas-Rachford and Peaceman-Rachford

The generalized Douglas-Rachford splitting introduced in [10] can be written as

$$y^{k+1} = (1 - \lambda_k)y^k + \lambda_k \frac{R_{\gamma F} R_{\gamma G} + I}{2} y^k, \quad \lambda_k \in (0, 2), \quad (1.5)$$

We have the usual DR splitting when $\lambda_k = 1$. In the limiting case $\lambda_k = 2$, (1.5) becomes the Peaceman-Rachford (PR) splitting

$$y^{k+1} = R_{\gamma F} R_{\gamma G} y^k. \quad (1.6)$$

Consider (1.5) with constant relaxation parameter $\lambda \in (0, 2]$ on (1.4). With the same assumptions and notations as in Theorem 1.2, assuming $\theta_1 \leq \frac{\pi}{4}$, we have the eventual linear convergence rate $\|y^k - y^*\| \leq C \rho(\theta_1, c, \lambda)^k$ where $c = \frac{\alpha}{\alpha+\gamma}$ and

$$\rho(\theta, c, \lambda) = \begin{cases} \sqrt{c \sin^2 \theta \lambda^2 - (1 - c \cos(2\theta))\lambda + 1}, & \text{if } c \geq \frac{1}{(\cos \theta + \sin \theta)^2} \\ \frac{1}{2} \left(\lambda c \cos(2\theta) - \lambda + 2 + \lambda \sqrt{\cos^2(2\theta)c^2 - 2c + 1} \right) & \text{if } c \leq \frac{1}{(\cos \theta + \sin \theta)^2} \end{cases}.$$

For fixed θ and c , the optimal relaxation parameter is

$$\lambda^*(\theta, c) = \arg \min_{\lambda} \rho(\theta, c, \lambda) = \begin{cases} 2 & \text{if } c \leq \bar{c} = \frac{1}{2 - \cos(2\theta)}, \\ \frac{1 - \cos 2\theta}{1 - \cos(2\theta)} & \text{if } c \geq \bar{c} \end{cases},$$

which is a continuous non-increasing function with respect to c and has range $(1, 2]$ for $c \in (0, 1)$.

The convergence rate at the optimal $\lambda = \lambda^*$ is

$$\rho(\theta, c, \lambda^*) = \begin{cases} c \cos(2\theta) + \sqrt{\cos^2(2\theta)c^2 - 2c + 1}, & \text{if } c \leq c^* = \frac{1}{(\cos \theta + \sin \theta)^2} \\ \sqrt{2c - 1}, & \text{if } c^* \leq c \leq \bar{c} = \frac{1}{2 - \cos(2\theta)}. \\ \frac{\sqrt{2c - 1 - c^2 \cos^2(2\theta)}}{2 \sin \theta \sqrt{c}}, & \text{if } c \geq \bar{c} \end{cases}.$$

See Figure 1.3 for the illustration of the asymptotic linear rate $\rho(\theta, c, \lambda)$. Several interesting facts can be seen immediately:

1. For Peaceman-Rachford splitting, i.e., (1.5) with $\lambda = 2$, if $c \geq c^*$, the asymptotic rate $\rho(\theta, c, 2) = \sqrt{2c - 1}$ is independent of θ .
2. For any $c < \bar{c} = \frac{1}{2 - \cos^2 \theta}$, we have $\rho(\theta, c, 2) < \rho(\theta, c, 1)$, i.e., the Peaceman-Rachford splitting has a better convergence rate than Douglas-Rachford.
3. The best possible rate of (1.5) is $\min_{c, \lambda} \rho(\theta, c, \lambda) = \rho(\theta, c^*, 2) = \frac{1 - \tan \theta}{1 + \tan \theta}$.

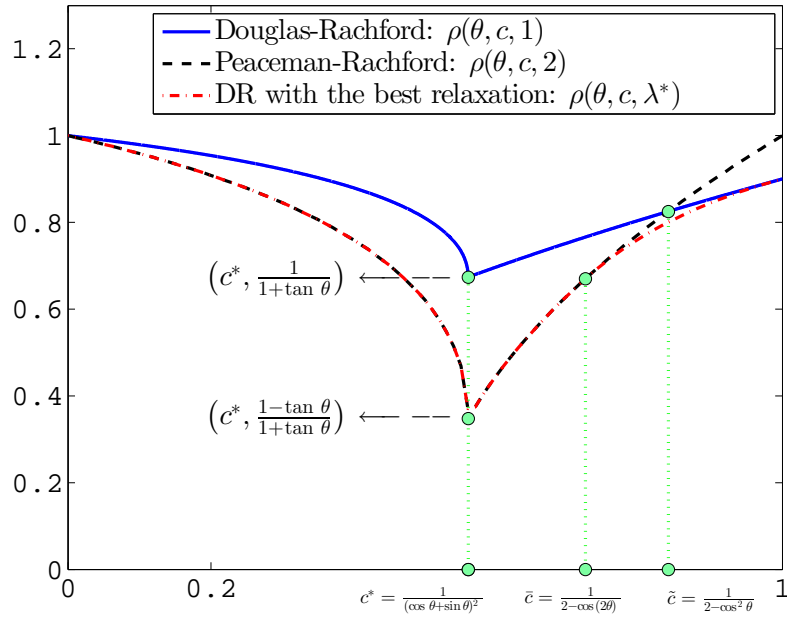


Figure 1.3: An illustration of eventual linear convergence rate for generalized Douglas-Rachford splitting with constant relaxation parameter λ on ℓ^2 -regularized basis pursuit: $\rho(\theta, c, \lambda)$ for a fixed θ . The vertical axis is $\rho(\theta, c, \lambda)$ and the horizontal axis is $c = \frac{\alpha}{\alpha + \gamma}$. For $c \leq \bar{c}$, the best relaxation parameter is $\lambda^* = 2$.

1.5 Context

There is neither strong convexity nor Lipschitz continuity in the objective function of (1.1) even locally around x^* , but any x^k with the same support as x^* lies on a low-dimensional manifold, on which the objective function $\|x\|_1$ is smooth. Such property is characterized as *partial smoothness* [24]. In other words, it is not surprising that nonsmooth optimization algorithms for (1.1) converge linearly if x^k has the correct support. For example, see [17, 29].

The main contribution of this paper is the quantification of the asymptotic linear convergence rate for Douglas-Rachford splitting on basis pursuit. It is well-known that Douglas-Rachford on the dual problem is the same as the alternating direction method of multipliers (ADMM) [13], which is also equivalent to split Bregman method [16]. Thus the analysis in this paper also applies to ADMM on the dual problem of ℓ^2 -regularized basis pursuit, i.e., the dual split Bregman method for basis pursuit [27]. By analyzing the generalized Douglas-Rachford introduced in [10] including the Peaceman-Rachford splitting, we obtain the explicit dependence of the asymptotic convergence rate on the parameters.

1.6 Contents

Details and proof of the main result will be shown in Section 2. In Sections 3, we apply the same methodology to obtain the asymptotic convergence rates for Douglas-Rachford,

generalized Douglas-Rachford and Peaceman-Rachford splittings on the ℓ^2 -regularized basis pursuit. In Section 4, we discuss the equivalence between Douglas-Rachford and dual split Bregman method, and their practical relevance. Numerical experiments illustrating the theorems are shown.

2 Douglas-Rachford for Basis Pursuit

2.1 Preliminaries

For any subspace \mathcal{X} in \mathbb{R}^n , we use $\mathbb{P}_{\mathcal{X}}(z)$ to denote the orthogonal projection onto \mathcal{X} of the point $z \in \mathbb{R}^n$.

In this section, we denote $F(x) = \partial\|x\|_1$, $G(x) = \partial\iota_{\{x:Ax=b\}}$, and the resolvents are $J_{\gamma F}(x) = S_{\gamma}(x)$ and $J_{\gamma G}(x) = P(x) = x + A^+(b - Ax)$. For convenience, we use $R = 2P - I$ to denote reflection about $Ax = b$, i.e., $R(x) = x + 2A^+(b - Ax)$. It is easy to see that R is idempotent. Then $T_{\gamma} = S_{\gamma} \circ R + I - P$.

Let $N(x^*)$ denote the set of coordinate indices associated with the nonzero components of x^* , namely, $N(x^*) \cup \{i_1, \dots, i_r\} = \{1, \dots, n\}$. Recall the definition of \mathcal{Q} in the previous section. Then for any $z \in \mathcal{Q}$, the soft thresholding operator can be written as $S_{\gamma}(z) = z - \gamma \sum_{j \in N(x^*)} \text{sgn}(x_j^*)e_j - B^+Bz$.

Lemma 2.1. *The assumption that x^* is the unique minimizer of (1.1) implies $\mathcal{N}(A) \cap \mathcal{N}(B) = \{\mathbf{0}\}$.*

Proof. Suppose there exists a nonzero vector $z \in \mathcal{N}(A) \cap \mathcal{N}(B)$. For any $\varepsilon \in \mathbb{R}$ with small magnitude, we have $\text{sgn}(x^* + \varepsilon z)^T = \text{sgn}(x^*)^T$ and $A(x^* + \varepsilon z) = b$. For nonzero small ε , the uniqueness of the minimizer implies $\|x^*\|_1 < \|x^* + \varepsilon z\|_1 = \text{sgn}(x^* + \varepsilon z)^T(x^* + \varepsilon z) = \text{sgn}(x^*)^T(x^* + \varepsilon z) = \|x^*\|_1 + \varepsilon \text{sgn}(x^*)^T z$. Thus $\text{sgn}(x^*)^T z \neq 0$.

On the other hand, for the function $h(\varepsilon) = \|x^* + \varepsilon z\|_1 = \|x^*\|_1 + \varepsilon \text{sgn}(x^*)^T z$ on a small neighborhood of $\varepsilon = 0$, the minimum of $h(\varepsilon)$ is $h(0)$, thus $\text{sgn}(x^*)^T z = h'(0) = 0$. This contradicts with the fact that $\text{sgn}(x^*)^T z \neq 0$. \square

The sum of the dimensions of $\mathcal{N}(A)$ and $\mathcal{N}(B)$ should be no larger than n since $\mathcal{N}(A) \cap \mathcal{N}(B) = \{\mathbf{0}\}$. Thus, $n - m + n - r \leq n$ implies $m \geq n - r$.

$\mathcal{N}(A) \cap \mathcal{N}(B) = \{\mathbf{0}\}$ also implies the orthogonal complement of the subspace spanned by $\mathcal{N}(A)$ and $\mathcal{N}(B)$ is $\mathcal{R}(A^T) \cap \mathcal{R}(B^T)$. Therefore, the dimension of $\mathcal{R}(A^T) \cap \mathcal{R}(B^T)$ is $m + r - n$.

2.2 Characterization of the fixed points of T_{γ}

Since $\partial\iota_{\{x:Ax=b\}} = \mathcal{R}(A^T)$, the first order optimality condition for (1.1) reads $0 \in \partial\|x^*\|_1 + \mathcal{R}(A^T)$, thus $\partial\|x^*\|_1 \cap \mathcal{R}(A^T) \neq \emptyset$. Any such $\eta \in \partial\|x^*\|_1 \cap \mathcal{R}(A^T)$ is called a dual certificate.

We have the following characterization of the fixed points of T_{γ} .

Lemma 2.2. *The set of the fixed points of T_{γ} can be described as*

$$\{y^* : y^* = x^* - \gamma\eta, \eta \in \partial\|x^*\|_1 \cap \mathcal{R}(A^T)\}.$$

Moreover, for any two fixed points y_1^* and y_2^* , we have $y_1^* - y_2^*, \mathbf{R}(y_1^*) - \mathbf{R}(y_2^*) \in \mathcal{R}(A^T) \cap \mathcal{R}(B^T)$. Thus there is a unique fixed point y^* if and only if $\mathcal{R}(A^T) \cap \mathcal{R}(B^T) = \{\mathbf{0}\}$.

Proof. For any $\eta \in \partial\|x^*\|_1 \cap \mathcal{R}(A^T)$, consider the vector $y^* = x^* - \gamma\eta$. Since $Ax^* = b$ and $A^+A\eta = \eta$ (implied by $\eta \in \mathcal{R}(A^T)$), we have $\mathbf{P}(y^*) = y^* + A^+(b - Ay^*) = x^* - \gamma\eta + A^+(b - Ax^* + A\gamma\eta) = x^* + A^+(b - Ax^*) = x^*$. Further, $\eta \in \partial\|x^*\|_1$ implies $S_\gamma(x^* + \gamma\eta) = x^*$. Thus $T_\gamma(y^*) = S_\gamma(2x^* - y^*) + y^* - x^* = S_\gamma(x^* + \gamma\eta) - x^* + y^* = y^*$.

Second, for any fixed point y^* of the operator T_γ , let $\eta = (x^* - y^*)/\gamma$. Then

$$\mathbf{P}(y^*) = x^*, \quad (\text{see Theorem 5 in [10]}) \quad (2.1)$$

implies $\eta = A^+A\eta$, thus $\eta \in \mathcal{R}(A^T)$. Further, $y^* = T_\gamma(y^*)$ implies $S_\gamma(x^* + \gamma\eta) = x^*$. We have $x^* = \arg \min_z \gamma\|z\|_1 + \frac{1}{2}\|z - (x^* + \gamma\eta)\|^2$, thus $\eta \in \partial\|x^*\|_1$.

Finally, let y_1^* and y_2^* be two fixed points. Then $y_1^* - y_2^* = -\gamma(\eta_1 - \eta_2)$ and $\mathbf{R}(y_1^*) - \mathbf{R}(y_2^*) = \gamma(\eta_1 - \eta_2)$ for some $\eta_1, \eta_2 \in \partial\|x^*\|_1 \cap \mathcal{R}(A^T)$. Notice that $\eta_1, \eta_2 \in \partial\|x^*\|_1$ implies $\eta_1 - \eta_2 \in \mathcal{R}(B^T)$. So we get $y_1^* - y_2^*, \mathbf{R}(y_1^*) - \mathbf{R}(y_2^*) \in \mathcal{R}(A^T) \cap \mathcal{R}(B^T)$. \square

With the assumption the matrix A has full row rank, the following condition is sufficient [12] and necessary [30] to ensure existence of a unique solution x^* to (1.1):

1. those columns of A with respect to the support of x^* are linearly independent.
2. there exists a dual certificate $\eta \in \partial\|x^*\|_1 \cap \mathcal{R}(A^T)$ such that $\mathbb{P}_{\mathcal{N}(B)}(\eta) = \text{sgn}(x^*)$ and $\|\mathbb{P}_{\mathcal{R}(B^T)}(\eta)\|_\infty < 1$.

Therefore, with assumption that there is a unique solution x^* to (1.1), there always exists a dual certificate $\eta \in \partial\|x^*\|_1 \cap \mathcal{R}(A^T)$ such that $\mathbb{P}_{\mathcal{N}(B)}(\eta) = \mathbb{P}_{\mathcal{N}(B)}(x^*)$ and $\|\mathbb{P}_{\mathcal{R}(B^T)}(\eta)\|_\infty < 1$. By Lemma 2.2, $y^* = x^* - \gamma\eta$ is a fixed point. And $\mathbf{R}(y^*)$ is in the interior of \mathcal{Q} since $\mathbf{R}(y^*) = \mathbf{R}(x^* - \gamma\eta) = x^* + \gamma\eta$.

We call a fixed point y^* an *interior fixed point* if $\mathbf{R}(y^*)$ is in the interior of the set \mathcal{Q} , or a *boundary fixed point* otherwise. A boundary fixed point exists only if $\mathcal{R}(A^T) \cap \mathcal{R}(B^T) \neq \{\mathbf{0}\}$.

Definition 2.3. Let \mathcal{U} and \mathcal{V} be two subspaces of \mathbb{R}^n with $\dim(\mathcal{U}) = p \leq \dim(\mathcal{V})$. The principal angles $\theta_k \in [0, \frac{\pi}{2}]$ ($k = 1, \dots, p$) between \mathcal{U} and \mathcal{V} are recursively defined by

$$\cos \theta_k = u_k^T v_k = \max_{u \in \mathcal{U}} \max_{v \in \mathcal{V}} u^T v,$$

$$\text{such that } \|u\| = \|v\| = 1, \quad u_j^T u = 0, \quad u_j^T v = 0, \quad j = 1, 2, \dots, k-1.$$

The vectors (u_1, \dots, u_p) and (v_1, \dots, v_p) are called *principal vectors*.

Lemma 2.4. Assume y^* is a boundary fixed point and $\mathbf{R}(y^*)$ lies on a L -dimensional face of the set \mathcal{Q} . Namely, there are L coordinates j_1, \dots, j_L such that $|\mathbf{R}(y^*)_{j_l}| = \gamma$ ($l = 1, \dots, L$). Recall that $B = [e_{i_1}, \dots, e_{i_r}]^T$, hence $\{j_1, \dots, j_L\}$ is a subset of $\{i_1, \dots, i_r\}$. Let B_1 denote the $(r-1) \times n$ matrix consisting of all row vectors of B except $[e_{j_1}]^T$. Recursively define B_l as the $(r-l) \times n$ matrix consisting of all row vectors of B_{l-1} except $[e_{j_l}]^T$ for $l = 2, \dots, L$. If there exists an index l such that $\mathcal{R}(A^T) \cap \mathcal{R}(B_l^T) = \mathbf{0}$, let M be the smallest such integer; otherwise, let $M = L$. Then $M \leq \dim[\mathcal{R}(A^T) \cap \mathcal{R}(B^T)]$, and the first principal angle between $\mathcal{N}(A)$ and $\mathcal{N}(B_l)$ ($l = 1, \dots, M$) is nonzero.

Proof. Let \mathcal{R}_l ($l = 1, \dots, L$) denote the one dimensional subspaces spanned by e_{j_l} , then $\mathcal{R}(B_{l-1}^T) = \mathcal{R}_l \oplus \mathcal{R}(B_l^T)$ and $\mathcal{N}(B_l) = \mathcal{R}_l \oplus \mathcal{N}(B_{l-1})$.

Let z^* be an interior fixed point. Notice that $|\mathbf{R}(y^*)_{j_l}| = \gamma$ and $|\mathbf{R}(z^*)_{j_l}| < \gamma$ for each $l = 1, \dots, L$, thus $\mathbb{P}_{\mathcal{R}_l}[\mathbf{R}(y^*) - \mathbf{R}(z^*)] = \mathbf{R}(y^*)_{j_l} - \mathbf{R}(z^*)_{j_l} \neq \mathbf{0}$. By Lemma 2.2 we have $\mathbf{R}(y^*) - \mathbf{R}(z^*) \in \mathcal{R}(A^T) \cap \mathcal{R}(B^T)$, therefore

$$\mathcal{R}_l \not\subseteq (\mathcal{R}(A^T) \cap \mathcal{R}(B^T))^\perp, \quad \forall l = 1, \dots, L. \quad (2.2)$$

Since $\mathcal{R}(B^T) = \mathcal{R}(B_1^T) \oplus \mathcal{R}_1 \oplus \dots \oplus \mathcal{R}_L$, with (2.2), we conclude that

$$\dim [\mathcal{R}(A^T) \cap \mathcal{R}(B_1^T)] \leq \dim [\mathcal{R}(A^T) \cap \mathcal{R}(B^T)] - 1.$$

Similarly, we have

$$\dim [\mathcal{R}(A^T) \cap \mathcal{R}(B_l^T)] \leq \dim [\mathcal{R}(A^T) \cap \mathcal{R}(B_{l-1}^T)] - 1, \quad l = 1, \dots, M.$$

Therefore,

$$\dim [\mathcal{R}(A^T) \cap \mathcal{R}(B_l^T)] \leq \dim [\mathcal{R}(A^T) \cap \mathcal{R}(B^T)] - l, \quad \forall l = 1, \dots, M, \quad (2.3)$$

thus $M \leq \dim [\mathcal{R}(A^T) \cap \mathcal{R}(B^T)]$.

Let $\mathcal{N}(A) \cup \mathcal{N}(B)$ denote the subspace spanned by $\mathcal{N}(A)$ and $\mathcal{N}(B)$. Since $\mathbb{R}^n = [\mathcal{R}(A^T) \cap \mathcal{R}(B^T)] \oplus [\mathcal{N}(A) \cup \mathcal{N}(B)] = [\mathcal{R}(A^T) \cap \mathcal{R}(B_l^T)] \oplus [\mathcal{N}(A) \cup \mathcal{N}(B_l)]$, by(2.3), we have $\dim [\mathcal{N}(A) \cup \mathcal{N}(B_l)] \geq \dim [\mathcal{N}(A) \cup \mathcal{N}(B)] + l = \dim [\mathcal{N}(A)] + \dim [\mathcal{N}(B)] + l = \dim [\mathcal{N}(A)] + \dim [\mathcal{N}(B_l)]$ for ($l = 1, \dots, M$). Therefore $\mathcal{N}(A) \cap \mathcal{N}(B_l) = \mathbf{0}$, and the first principal angle between $\mathcal{N}(A)$ and $\mathcal{N}(B_l)$ is nonzero. \square

2.3 The characterization of the operator T_γ

Lemma 2.5. *For any y satisfying $\mathbf{R}(y) \in \mathcal{Q}$ and any fixed point y^* , $T_\gamma(y) - T_\gamma(y^*) = [(I_n - B^+B)(I_n - A^+A) + B^+BA^+A](y - y^*)$ where I_n denotes the $n \times n$ identity matrix.*

Proof. First, we have

$$\begin{aligned} T_\gamma(y) &= [S_\gamma \circ (2P - I) + I - P](y) = S_\gamma(\mathbf{R}(y)) + y - P(y) \\ &= \mathbf{R}(y) - \gamma \sum_{j \in N(x^*)} e_j \operatorname{sgn}(x_j^*) - B^+B\mathbf{R}(y) + y - P(y) \\ &= P(y) - \gamma \sum_{j \in N(x^*)} e_j \operatorname{sgn}(x_j^*) - B^+B\mathbf{R}(y). \end{aligned}$$

The last step is due to the fact $\mathbf{R} = 2P - I$. The definition of fixed points and (2.1) imply

$$S_\gamma(\mathbf{R}(y^*)) = x^*, \quad (2.4)$$

thus $\mathbf{R}(y^*) \in \mathcal{Q}$. So we also have

$$T_\gamma(y^*) = P(y^*) - \gamma \sum_{j \in N(x^*)} e_j \operatorname{sgn}(x_j^*) - B^+B\mathbf{R}(y^*).$$

Let $v = y - y^*$, then

$$\begin{aligned}
T_\gamma(y) - T_\gamma(y^*) &= P(y) - B^+BR(y) - [P(y^*) - B^+BR(y^*)] \\
&= y + A^+(b - Ay) - B^+B(y + 2A^+(b - Ay)) \\
&\quad - [y^* + A^+(b - Ay^*) - B^+B(y^* + 2A^+(b - Ay^*))] \\
&= v - A^+Av - B^+Bv + 2B^+BA^+Av \\
&= [(I_n - B^+B)(I_n - A^+A) + B^+BA^+A]v.
\end{aligned}$$

□

We now study the matrix

$$\mathbf{T} = (I_n - B^+B)(I_n - A^+A) + B^+BA^+A. \quad (2.5)$$

Let A_0 be a $n \times (n - m)$ matrix whose column vectors form an orthonormal basis of $\mathcal{N}(A)$ and A_1 be a $n \times m$ matrix whose column vectors form an orthonormal basis of $\mathcal{R}(A^T)$. Since A^+A represents the projection to $\mathcal{R}(A^T)$ and so is $A_1A_1^T$, we have $A^+A = A_1A_1^T$. Similarly, $I_n - A^+A = A_0A_0^T$. Let B_0 and B_1 be similarly defined for $\mathcal{N}(B)$ and $\mathcal{R}(B^T)$. The matrix \mathbf{T} can now be written as

$$\mathbf{T} = B_0B_0^T A_0A_0^T + B_1B_1^T A_1A_1^T.$$

It will be convenient to study the norm of the matrix \mathbf{T} in terms of principal angles between subspaces.

Without loss of generality, we assume $n - r \leq n - m$. Let θ_i ($i = 1, \dots, n - r$) be the principal angles between the subspaces $\mathcal{N}(A)$ and $\mathcal{N}(B)$. Then the first principal angle $\theta_1 > 0$ since $\mathcal{N}(A) \cap \mathcal{N}(B) = \mathbf{0}$. Let $\cos \Theta$ denote the $(n - r) \times (n - r)$ diagonal matrix with the diagonal entries $(\cos \theta_1, \dots, \cos \theta_{(n-r)})$.

The singular value decomposition (SVD) of the $(n - r) \times (n - m)$ matrix $E_0 = B_0^T A_0$ is $E_0 = U_0 \cos \Theta V^T$ with $U_0^T U_0 = V^T V = I_{(n-r)}$, and the column vectors of $B_0 U_0$ and $A_0 V$ give the principal vectors, see Theorem 1 in [3].

By the definition of SVD, V is a $(n - m) \times (n - r)$ matrix and its column vectors are orthonormalized. Let V' be a $(n - m) \times (r - m)$ matrix whose column vectors are normalized and orthogonal to those of V . For the matrix $\tilde{V} = (V, V')$, we have $I_{(n-m)} = \tilde{V} \tilde{V}^T$. For the matrix $E_1 = B_1^T A_0$, consider $E_1^T E_1 = A_0^T B_1 B_1^T A_0$. Since $B_0 B_0^T + B_1 B_1^T = I_n$, we have $E_1^T E_1 = A_0^T A_0 - A_0^T B_0 B_0^T A_0 = I_{(n-m)} - V \cos^2 \Theta V^T = (V, V') \begin{pmatrix} \sin^2 \Theta & 0 \\ 0 & I_{(r-m)} \end{pmatrix} (V, V')^T$, so the SVD of E_1 can be written as

$$B_1^T A_0 = E_1 = U_1 \begin{pmatrix} \sin \Theta & 0 \\ 0 & I_{(r-m)} \end{pmatrix} \tilde{V}^T. \quad (2.6)$$

Notice that $A_0 = B_0 B_0^T A_0 + B_1 B_1^T A_0 = B_0 E_0 + B_1 E_1$, so we have

$$\begin{aligned}
A_0 A_0^T &= (B_0, B_1) \begin{pmatrix} E_0 E_0^T & E_0 E_1^T \\ E_1 E_0^T & E_1 E_1^T \end{pmatrix} (B_0, B_1)^T \\
&= (B_0 U_0, B_1 U_1) \left(\begin{array}{c|cc} \cos^2 \Theta & \cos \Theta \sin \Theta & 0 \\ \cos \Theta \sin \Theta & \sin^2 \Theta & 0 \\ \hline 0 & 0 & I_{(r-m)} \end{array} \right) (B_0 U_0, B_1 U_1)^T. \quad (2.7)
\end{aligned}$$

Let \mathcal{C} denote the orthogonal complement of $\mathcal{R}(A^T) \cap \mathcal{R}(B^T)$ in the subspace $\mathcal{R}(B^T)$, namely, $\mathcal{R}(B^T) = [\mathcal{R}(A^T) \cap \mathcal{R}(B^T)] \oplus \mathcal{C}$. Then the dimension of \mathcal{C} is $n - m$. Let $\tilde{B}_0 = B_0 U_0$ and $\tilde{B}_1 = B_1 U_1$, then the column vectors of \tilde{B}_0 form an orthonormal basis of $\mathcal{N}(B)$. The column vectors of \tilde{B}_1 are a family of orthonormal vectors in $\mathcal{R}(B^T)$. Moreover, the SVD (2.6) implies the columns of \tilde{B}_1 and $A_0 \tilde{V}$ are principal vectors corresponding to angles $\{\frac{\pi}{2} - \theta_1, \dots, \frac{\pi}{2} - \theta_{(n-r)}, 0, \dots, 0\}$ between the two subspaces $\mathcal{R}(B^T)$ and $\mathcal{N}(A)$, see [3]. And $\theta_1 > 0$ implies the largest angle between $\mathcal{R}(B^T)$ and $\mathcal{N}(A)$ is less than $\pi/2$, so none of the column vectors of \tilde{B}_1 is orthogonal to $\mathcal{N}(A)$ thus all the column vectors of \tilde{B}_1 are in the subspace \mathcal{C} . By counting the dimension of \mathcal{C} , we know that column vectors of \tilde{B}_1 form an orthonormal basis of \mathcal{C} .

Let \tilde{B}_2 be a $n \times (r+m-n)$ whose columns form an orthonormal basis of $\mathcal{R}(A^T) \cap \mathcal{R}(B^T)$, then we have

$$A_0 A_0^T = (\tilde{B}_0, \tilde{B}_1, \tilde{B}_2) \begin{pmatrix} \cos^2 \Theta & \cos \Theta \sin \Theta & 0 & 0 \\ \cos \Theta \sin \Theta & \sin^2 \Theta & 0 & 0 \\ 0 & 0 & I_{(r-m)} & 0 \\ 0 & 0 & 0 & 0_{(r+m-n)} \end{pmatrix} \begin{pmatrix} \tilde{B}_0^T \\ \tilde{B}_1^T \\ \tilde{B}_2^T \end{pmatrix}.$$

Since $(\tilde{B}_0, \tilde{B}_1, \tilde{B}_2)$ is a unitary matrix and $A_1 A_1^T = I_n - A_0 A_0^T$, we also have

$$A_1 A_1^T = (\tilde{B}_0, \tilde{B}_1, \tilde{B}_2) \begin{pmatrix} \sin^2 \Theta & -\cos \Theta \sin \Theta & 0 & 0 \\ -\cos \Theta \sin \Theta & \cos^2 \Theta & 0 & 0 \\ 0 & 0 & 0_{(r-m)} & 0 \\ 0 & 0 & 0 & I_{(r+m-n)} \end{pmatrix} \begin{pmatrix} \tilde{B}_0^T \\ \tilde{B}_1^T \\ \tilde{B}_2^T \end{pmatrix}. \quad (2.8)$$

Therefore, we get the decomposition

$$\begin{aligned} \mathbf{T} &= B_0 B_0^T A_0 A_0^T + B_1 B_1^T A_1 A_1^T \\ &= (\tilde{B}_0, \tilde{B}_1, \tilde{B}_2) \begin{pmatrix} \cos^2 \Theta & \cos \Theta \sin \Theta & 0 & 0 \\ -\cos \Theta \sin \Theta & \cos^2 \Theta & 0 & 0 \\ 0 & 0 & 0_{(r-m)} & 0 \\ 0 & 0 & 0 & I_{(r+m-n)} \end{pmatrix} \begin{pmatrix} \tilde{B}_0^T \\ \tilde{B}_1^T \\ \tilde{B}_2^T \end{pmatrix}. \end{aligned} \quad (2.9)$$

2.4 Standard cases: the interior fixed points

Assume the sequence y^k will converge to an interior fixed point.

First, consider the simple case when $\mathcal{R}(A^T) \cap \mathcal{R}(B^T) = \{\mathbf{0}\}$, then $m + r = n$ and the fixed point is unique and interior. Let $\mathcal{B}_a(z)$ denote the ball centered at z with radius a . Let ε be the largest number such that $\mathcal{B}_\varepsilon(\mathcal{R}(y^*)) \subseteq \mathcal{Q}$. Let K be the smallest integer such that $y^K \in \mathcal{B}_\varepsilon(y^*)$ (thus $\mathcal{R}(y^K) \in \mathcal{B}_\varepsilon(\mathcal{R}(y^*))$). By nonexpansiveness of T_γ and \mathcal{R} , we get $\mathcal{R}(y^k) \in \mathcal{B}_\varepsilon(\mathcal{R}(y^*))$ for any $k \geq K$. By a recursive application of Lemma 2.5, we have

$$T_\gamma(y^k) - y^* = \mathbf{T}(T_\gamma(y^{k-1}) - y^*) = \dots = \mathbf{T}^{k-K}(y^K - y^*), \quad \forall k > K.$$

Now, (2.9) and $\mathcal{R}(A^T) \cap \mathcal{R}(B^T) = \{\mathbf{0}\}$ imply $\|\mathbf{T}\|_2 = \cos \theta_1$. Notice that \mathbf{T} is normal, so we have $\|\mathbf{T}^q\|_2 = \|\mathbf{T}\|_2^q$ for any positive integer q . Thus we get the convergence rate for large k :

$$\|T_\gamma(y^k) - y^*\|_2 \leq (\cos \theta_1)^{k-K} \|y^K - y^*\|_2, \quad \forall k > K. \quad (2.10)$$

If $\mathcal{R}(A^T) \cap \mathcal{R}(B^T) \neq \{\mathbf{0}\}$, then there are many fixed points by Lemma 2.2. Let \mathcal{I} be the set of all interior fixed points. For $z^* \in \mathcal{I}$, let $\varepsilon(z^*)$ be the largest number such that $\mathcal{B}_{\varepsilon(z^*)}(\mathcal{R}(z^*)) \subseteq \mathcal{Q}$.

If $y^K \in \bigcup_{z^* \in \mathcal{I}} \mathcal{B}_{\varepsilon(z^*)}(z^*)$ for some K , then consider the Euclidean projection of y^K to \mathcal{I} , denoted by y^* . Then $\mathbb{P}_{\mathcal{R}(A^T) \cap \mathcal{R}(B^T)}(y^K - y^*) = \mathbf{0}$ since $y_1^* - y_2^* \in \mathcal{R}(A^T) \cap \mathcal{R}(B^T)$ for any $y_1^*, y_2^* \in \mathcal{I}$. By (2.9), $\mathcal{R}(A^T) \cap \mathcal{R}(B^T)$ is the eigenspace of eigenvalue 1 for the matrix \mathbf{T} . So we have $\|\mathbf{T}(y^K - y^*)\| \leq \cos \theta_1 \|y^K - y^*\|$, thus the error estimate (2.10) still holds.

The sequence y^k may converge to a different fixed points for each initial value y^0 ; the fixed point y^* is the projection of y^K to \mathcal{I} . Here K is the smallest integer such that $y^K \in \bigcup_{z^* \in \mathcal{I}} \mathcal{B}_{\varepsilon(z^*)}(\mathcal{R}(z^*))$.

Theorem 2.6. *For the algorithm (1.2) solving (1.1), if y^k converges to an interior fixed point, then there exists an integer K such that (2.10) holds.*

2.5 Nonstandard cases: the boundary fixed points

Suppose y^k converges to a boundary fixed point y^* . With the same notations in Lemma 2.4, for simplicity, we only discuss the case $M = 1$. More general cases can be discussed similarly. Without loss of generality, assume $j_1 = 1$ and $\mathcal{R}(y^*)_1 = \gamma$. Then the set \mathcal{Q} is equal to $Q_1 \oplus Q_2 \oplus \cdots \oplus Q_n$, with $Q_1 = [-\gamma, \gamma]$. Consider another set $\mathcal{Q}_1 = (\gamma, +\infty) \oplus Q_2 \oplus \cdots \oplus Q_n$. Any neighborhood of $\mathcal{R}(y^*)$ intersects both \mathcal{Q} and \mathcal{Q}_1 .

There are three cases:

- I. the sequence $\mathcal{R}(y^k)$ stays in \mathcal{Q} if k is large enough,
- II. the sequence $\mathcal{R}(y^k)$ stays in \mathcal{Q}_1 if k is large enough,
- III. for any K , there exists $k_1, k_2 > K$ such that $\mathcal{R}(y^{k_1}) \in \mathcal{Q}$ and $\mathcal{R}(y^{k_2}) \in \mathcal{Q}_1$.

Case I. Assume y^k converges to y^* and $\mathcal{R}(y^k)$ stay in \mathcal{Q} for any $k \geq K$. Then $\mathbb{P}_{\mathcal{R}(A^T) \cap \mathcal{R}(B^T)}(y^K - y^*)$ must be zero. Otherwise, by (2.9), we have $\lim_{k \rightarrow \infty} y^k - y^* = \mathbb{P}_{\mathcal{R}(A^T) \cap \mathcal{R}(B^T)}(y^K - y^*) \neq \mathbf{0}$. By (2.9), the eigenspace of \mathbf{T} associated with the eigenvalue 1 is $\mathcal{R}(A^T) \cap \mathcal{R}(B^T)$, so (2.10) still holds.

Case II Assume y^k converges to y^* and $\mathcal{R}(y^k)$ stay in \mathcal{Q}_1 for any $k \geq K$. Let $\bar{B} = [e_{i_2}, \cdots, e_{i_r}]^T$. Following Lemma 2.5, for any y satisfying $\mathcal{R}(y) \in \mathcal{Q}_1$, we have $T_\gamma(y) - T_\gamma(y^*) = [(I_n - \bar{B}^+ \bar{B})(I_n - A^+ A) + \bar{B}^+ \bar{B} A^+ A](y - y^*)$.

Without loss of generality, assume $n - r + 1 \leq n - m$. Consider the $(n - r + 1)$ principal angles between $\mathcal{N}(A)$ and $\mathcal{N}(\bar{B})$ denoted by $(\bar{\theta}_1, \cdots, \bar{\theta}_{(n-r+1)})$. Let $\bar{\Theta}_1$ denote the diagonal matrix with diagonal entries $(\bar{\theta}_1, \cdots, \bar{\theta}_{(n-r+1)})$. Then the matrix $\bar{\mathbf{T}} = (I_n - \bar{B}^+ \bar{B})(I_n - A^+ A) + \bar{B}^+ \bar{B} A^+ A$ can be written as

$$\bar{\mathbf{T}} = (\tilde{B}_0, \tilde{B}_1, \tilde{B}_2) \left(\begin{array}{ccc|c} \cos^2 \Theta_1 & \cos \Theta_1 \sin \Theta_1 & 0 & 0 \\ -\cos \Theta_1 \sin \Theta_1 & \cos^2 \Theta_1 & 0 & 0 \\ 0 & 0 & 0_{(r-m-1)} & 0 \\ 0 & 0 & 0 & I_{(r+m-n-1)} \end{array} \right) \begin{pmatrix} \tilde{B}_0^T \\ \tilde{B}_1^T \\ \tilde{B}_2^T \end{pmatrix}, \quad (2.11)$$

where $(\tilde{B}_0, \tilde{B}_1, \tilde{B}_2)$ are redefined accordingly.

By Lemma 2.4, $\bar{\theta}_1 > 0$. Following the first case, we have $\mathbb{P}_{\mathcal{R}(A^T) \cap \mathcal{R}(\bar{B}^T)}(y^K - y^*) = \mathbf{0}$. So

$$\|T_\gamma(y^k) - y^*\|_2 \leq (\cos \bar{\theta}_1)^{k-K} \|y^K - y^*\|_2, \quad \forall k > K.$$

Convergence is slower than previously, as $\bar{\theta}_1 \leq \theta_1$.

Case III Assume y^k converges to y^* and $R(y^k)$ stay in $\mathcal{Q} \cup \mathcal{Q}_1$ for any $k \geq K$. Then $\mathbb{P}_{\mathcal{R}(A^T) \cap \mathcal{R}(\bar{B}^T)}(y^K - y^*) = \mathbf{0}$. And for $R(y^k) \in \mathcal{Q}_1$ we have $\|T_\gamma(y^k) - y^*\|_2 \leq (\cos \bar{\theta}_1) \|y^k - y^*\|_2$. Let \mathcal{D} be the orthogonal complement of $\mathcal{R}(A^T) \cap \mathcal{R}(\bar{B}^T)$ in $\mathcal{R}(A^T) \cap \mathcal{R}(B^T)$, namely $\mathcal{R}(A^T) \cap \mathcal{R}(B^T) = \mathcal{R}(A^T) \cap \mathcal{R}(\bar{B}^T) \oplus \mathcal{D}$. For $y^k \in \mathcal{Q}$, we have $\|\mathbb{P}_{\mathcal{D}^\perp}(T_\gamma(y^k) - y^*)\|_2 \leq \cos \theta_1 \|\mathbb{P}_{\mathcal{D}^\perp}(y^k - y^*)\|_2$ and $\mathbb{P}_{\mathcal{D}}(T_\gamma(y^k) - y^*) = \mathbb{P}_{\mathcal{D}}(y^k - y^*)$.

For the Case III, which we refer to as nongeneric cases, no convergence results like $\|T_\gamma(y^k) - y^*\|_2 \leq (\cos \bar{\theta}_1) \|y^k - y^*\|_2$ can be established since $\mathbb{P}_{\mathcal{D}}(T_\gamma(y^k) - y^*) = \mathbb{P}_{\mathcal{D}}(y^k - y^*)$ whenever $R(y^k) \in \mathcal{Q}$. Even though it seems hard to exclude Case III from the analysis, it has not been observed in our numerical tests.

2.6 Generalized Douglas-Rachford

Consider the generalized Douglas-Rachford splitting (1.5) with constant relaxation parameter:

$$\begin{cases} y^{k+1} = y^k + \lambda [S_\gamma(2x^k - y^k) - x^k] \\ x^{k+1} = y^{k+1} + A^+(b - Ay^{k+1}) \end{cases}, \quad \lambda \in (0, 2). \quad (2.12)$$

Let $T_\gamma^\lambda = \mathbf{I} + \lambda [S_\gamma \circ (2\mathbf{P} - \mathbf{I}) - \mathbf{P}]$. Then any fixed point y^* of T_γ^λ satisfies $\mathbf{P}(y^*) = x^*$, [8]. So the fixed points set of T_γ^λ is the same as the fixed points set of T_γ . Moreover, for any y satisfying $R(y) \in \mathcal{Q}$ and any fixed point y^* , $T_\gamma^\lambda(y) - T_\gamma^\lambda(y^*) = [I_n + \lambda(I_n - B^+B)(I_n - 2A^+A) - \lambda(I_n - A^+A)](y - y^*)$.

To find the asymptotic convergence rate of (2.12), it suffices to consider the matrix $\mathbf{T}_\lambda = I_n + \lambda(I_n - B^+B)(I_n - 2A^+A) - \lambda(I_n - A^+A) = (1 - \lambda)I_n + \lambda\mathbf{T}$. By (2.9), we have

$$\mathbf{T}_\lambda = \tilde{B} \left(\begin{array}{ccc|ccc} \cos^2 \Theta + (1 - \lambda) \sin^2 \Theta & & & \lambda \cos \Theta \sin \Theta & & 0 & & 0 \\ -\lambda \cos \Theta \sin \Theta & & & \cos^2 \Theta + (1 - \lambda) \sin^2 \Theta & & 0 & & 0 \\ & 0 & & 0 & & (1 - \lambda)I_{(r-m)} & & 0 \\ & 0 & & 0 & & 0 & & I_{(r+m-n)} \end{array} \right) \tilde{B}^T,$$

where $\tilde{B} = (\tilde{B}_0, \tilde{B}_1, \tilde{B}_2)$.

Notice that \mathbf{T}_λ is a normal matrix. By the discussion in Section 2, if y^k in the iteration of (2.12) converges to an interior fixed point, the asymptotic convergence rate will be governed by the matrix

$$\mathbf{M}_\lambda = \left(\begin{array}{ccc|ccc} \cos^2 \Theta + (1 - \lambda) \sin^2 \Theta & & & \lambda \cos \Theta \sin \Theta & & 0 \\ -\lambda \cos \Theta \sin \Theta & & & \cos^2 \Theta + (1 - \lambda) \sin^2 \Theta & & 0 \\ & 0 & & 0 & & (1 - \lambda)I_{(r-m)} \end{array} \right).$$

Note that $\|\mathbf{M}_\lambda\| = \sqrt{\lambda(2 - \lambda) \cos^2 \theta_1 + (1 - \lambda)^2} \geq \cos \theta_1$ for any $\lambda \in (0, 2)$. Therefore, the asymptotic convergence rate of (2.12) is always slower than (1.3) if $\lambda \neq 1$. We emphasize that this does not mean (1.3) is more efficient than (2.12) for x^k to reach a given accuracy.

2.7 Relation to the Restricted Isometry Property

Let A be a $m \times n$ random matrix and each column of A is normalized, i.e., $\sum_i A_{ij}^2 = 1$ for each j . The Restricted Isometry Property (RIP) introduced in [5] is as follows.

Definition 2.7. For each integer $s = 1, 2, \dots$, the restricted isometry constants δ_s of A is the smallest number such that

$$(1 - \delta_s)\|x\|^2 \leq \|Ax\|^2 \leq (1 + \delta_s)\|x\|^2, \quad (2.13)$$

holds for all vectors x with at most s nonzero entries.

In particular, any vector with the same support as x^* can be denoted as $(I_n - B^+B)x$ for some $x \in \mathbb{R}^n$. The RIP (2.13) with $s = n - r$ implies

$$(1 - \delta_{(n-r)})\|(I_n - B^+B)x\|^2 \leq \|A(I_n - B^+B)x\|^2 \leq (1 + \delta_{(n-r)})\|(I_n - B^+B)x\|^2, \quad \forall x \in \mathbb{R}^n.$$

Let d denote the smallest eigenvalue of $(AA^T)^{-1}$. Then $d > 0$ since we assume A has full row rank. For any vector y , we have

$$\|A^+Ay\|^2 = y^T A^T [(AA^T)^{-1}]^T AA^T (AA^T)^{-1} Ay = y^T A^T [(AA^T)^{-1}]^T Ay \geq d\|Ay\|^2,$$

where the last step is due to the Courant–Fischer–Weyl min-max principle.

Therefore, we get

$$\|A^+A(I_n - B^+B)x\|^2 \geq d\|A(I_n - B^+B)x\|^2 \geq d(1 - \delta_{(n-r)})\|(I_n - B^+B)x\|^2, \quad \forall x \in \mathbb{R}^n, \quad (2.14)$$

We will show that (2.14) gives a lower bound of the first principal angle θ_1 between two subspaces $\mathcal{N}(A)$ and $\mathcal{N}(B)$. Notice that (2.8) implies

$$A^+A(I_n - B^+B) = A_1 A_1^T B_0 B_0^T = (B_0 U_0, B_1 U_1) \begin{pmatrix} \sin^2 \Theta & | & 0 \\ -\cos \Theta \sin \Theta & | & 0 \\ 0 & | & 0 \end{pmatrix} (B_0 U_0, B_1 U_1)^T,$$

by which we have $\|A^+A(I_n - B^+B)x\|^2 = x^T (B_0 U_0, B_1 U_1) \begin{pmatrix} \sin^2 \Theta & | & 0 \\ 0 & | & 0 \end{pmatrix} (B_0 U_0, B_1 U_1)^T x$.

Let $z = (B_0 U_0, B_1 U_1)^T x$. Since $I_n - B^+B = (B_0 U_0, B_1 U_1) \begin{pmatrix} I_{(n-r)} & | & 0 \\ 0 & | & 0 \end{pmatrix} (B_0 U_0, B_1 U_1)^T$, (2.14) is equivalent to

$$z^T \begin{pmatrix} \sin^2 \Theta & | & 0 \\ 0 & | & 0 \end{pmatrix} z \geq d(1 - \delta_{(n-r)}) z^T \begin{pmatrix} I_{n-r} & | & 0 \\ 0 & | & 0 \end{pmatrix} z, \quad \forall z \in \mathbb{R}^n,$$

which implies $\sin^2 \theta_1 \geq d(1 - \delta_{(n-r)})$ by the Courant–Fischer–Weyl min-max principle. So the RIP constant gives us

$$\cos \theta_1 \leq \sqrt{1 - d(1 - \delta_{(n-r)})}.$$

2.8 Numerical examples

We consider several examples for (1.3). In all the examples, $y^0 = \mathbf{0}$ unless specified otherwise. For examples in this subsection, the angles between the null spaces can be computed by singular value decomposition (SVD) of $A_0^T B_0$ [3].

Example 1 The matrix A is a 3×40 random matrix with standard normal distribution and x^* has three nonzero components. By counting dimensions, we know that $\mathcal{R}(A^T) \cap \mathcal{R}(B^T) = \{\mathbf{0}\}$. Therefore there is only one fixed point. See Figure 1.1 for the error curve of x^k and y^k with $\gamma = 1$. Obviously, the error $\|x^k - x^*\|$ is not monotonically decreasing but $\|y^k - y^*\|$ is since the operator T_γ is non-expansive. And the slope of $\log \|y^k - y^*\|$ is exactly $\log(\cos \theta_1) = \log(0.9932)$ for large k .

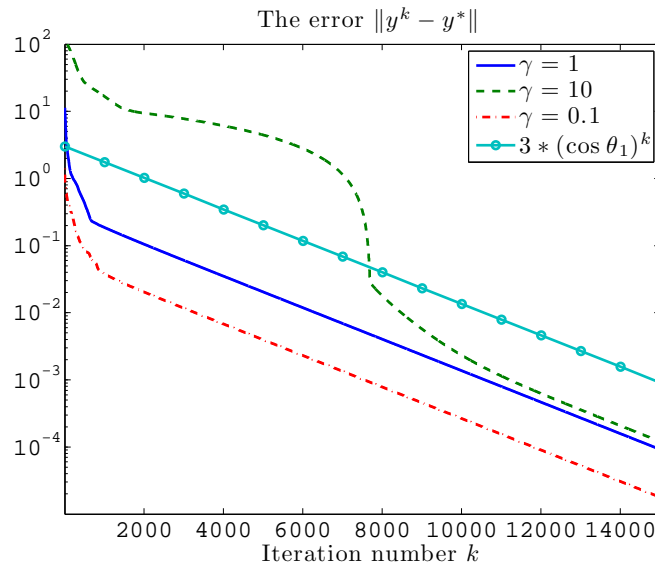


Figure 2.1: Example 2: for an interior fixed point, the asymptotic rate remains the same for different soft-thresholding parameter γ . The slope of the straight line is $\log(\cos \theta_1)$.

Example 2 The matrix A is a 10×1000 random matrix with standard normal distribution and x^* has ten nonzero components. Thus there is only one fixed point. See Figure 2.1 for the error curve of y^k with $\gamma = 0.1, 1, 10$. We take y^* as the result of (1.3) after 8×10^4 iterations. The slopes of $\log \|y^k - y^*\|$ for different γ are exactly $\log(\cos \theta_1) = \log(0.9995)$ for large k .

Example 3 The matrix A is a 18×100 submatrix of a 100×100 Fourier matrix and x^* has two nonzero components. There are interior and boundary fixed points. In this example, we fix $\gamma = 1$ and test (1.3) with random y^0 for six times. See Figure 2.2 for the error curve of x^k . In Figure 2.2, in four tests, y^k converges to an interior fix point, thus the convergence rate for large k is governed by $\cos \theta_1 = 0.9163$. In the second and third tests, y^k converges to

different boundary fixed points¹ thus convergence rates are slower than $\cos \theta_1$. Nonetheless, the rate for large k is still linear.

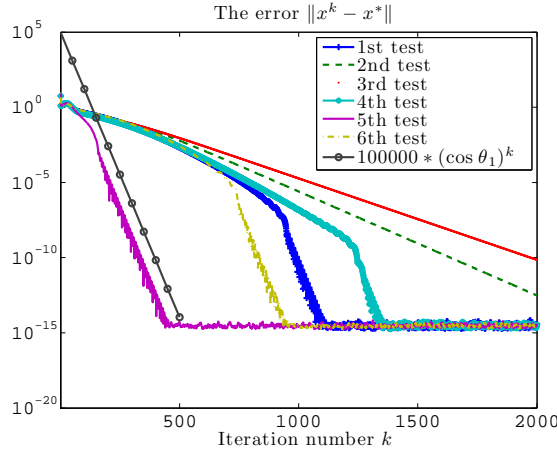


Figure 2.2: Example 3: fixed $\gamma = 1$ with random y^0 .

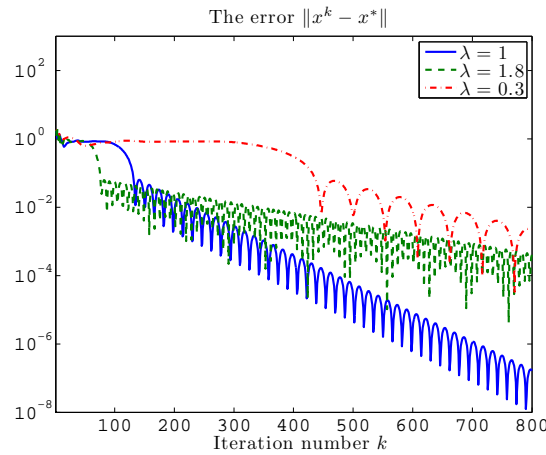


Figure 2.3: Example 4: The Generalized Douglas-Rachford (2.12) with different λ and fixed $\gamma = 1$. The asymptotic convergence rate of (1.3) ($\lambda = 1$) is the fastest.

Example 4 The matrix A is a 5×40 random matrix with standard normal distribution and x^* has three nonzero components. See Figure 2.3 for the comparison of (1.3) and (2.12) with $\gamma = 1$.

Remark 2.8. To apply Douglas-Rachford splitting (1.2) to basis pursuit (1.1), we can also

¹At least, numerically so in double precision.

choose $g(x) = \|x\|_1$ and $f(x) = \iota_{\{x:Ax=b\}}$, then Douglas-Rachford iterations become

$$\begin{cases} y^{k+1} = x^k + A^+(b - A(2x^k - y^k)) \\ x^{k+1} = S_\gamma(y^{k+1}) \end{cases} \quad (2.15)$$

The discussion in this section can be applied to (2.15). In particular, the corresponding matrix in (2.5) is $\mathbf{T} = (I_n - A^+A)(I_n - B^+B) + A^+AB^+B$, thus all the asymptotic convergence rates remain valid. For all the numerical tests in this paper, we did not observe any significant difference in performance between (1.3) and (2.15).

3 The ℓ^2 regularized Basis Pursuit

3.1 Preliminaries

For the ℓ^2 regularized Basis Pursuit (1.4), to use Douglas-Rachford splitting (1.2) to solve the equivalent problem $\min_x \|x\|_1 + \iota_{\{x:Ax=b\}} + \frac{1}{2\alpha}\|x\|^2$, there are quite a few splitting choices:

1.

$$f(x) = \|x\|_1 + \frac{1}{2\alpha p}\|x\|^2, \quad g(x) = \iota_{\{x:Ax=b\}} + \frac{1}{2\alpha q}\|x\|^2, \quad \forall p, q \geq 1, \frac{1}{p} + \frac{1}{q} = 1. \quad (3.1)$$

2.

$$g(x) = \|x\|_1 + \frac{1}{2\alpha p}\|x\|^2, \quad f(x) = \iota_{\{x:Ax=b\}} + \frac{1}{2\alpha q}\|x\|^2, \quad \forall p, q \geq 1, \frac{1}{p} + \frac{1}{q} = 1. \quad (3.2)$$

The following two resolvents will be needed:

- $h(x) = \|x\|_1 + \frac{1}{2\alpha}\|x\|^2$, $J_{\gamma\partial h}(x) = \arg \min_z \gamma\|z\|_1 + \frac{\gamma}{2\alpha}\|z\|^2 + \frac{1}{2}\|z - x\|^2 = \frac{\alpha}{\alpha+\gamma}S_\gamma(x)$.
- $h(x) = \iota_{\{x:Ax=b\}} + \frac{1}{2\alpha}\|x\|^2$, $J_{\gamma\partial h}(x) = \arg \min_z \gamma\iota_{\{z:Az=b\}} + \frac{\gamma}{2\alpha}\|z\|^2 + \frac{1}{2}\|z - x\|^2 = \frac{\alpha}{\alpha+\gamma}x + A^+(b - \frac{\alpha}{\alpha+\gamma}Ax)$.

3.2 Douglas-Rachford splitting

In particular, Douglas-Rachford splitting (1.2) using (3.1) with $p = 1$ and $q = \infty$ is equivalent to the dual split Bregman method [27]. See Section 4.3 for the equivalence. We first discuss this special case.

Let $f(x) = \|x\|_1 + \frac{1}{2\alpha}\|x\|^2$ and $g(x) = \iota_{\{x:Ax=b\}}$, the Douglas-Rachford splitting (1.2) for (1.1) reads

$$\begin{cases} y^{k+1} = \frac{\alpha}{\alpha+\gamma}S_\gamma(2x^k - y^k) + y^k - x^k \\ x^{k+1} = y^{k+1} + A^+(b - Ay^{k+1}) \end{cases} \quad (3.3)$$

Since $\|x\|_1 + \frac{1}{2\alpha}\|x\|^2$ is a strongly convex function, (1.4) always has a unique minimizer x^* as long as $\{x : Ax = b\}$ is nonempty. The first order optimality condition $\mathbf{0} \in \partial F(x^*) + \partial G(x^*)$ implies the dual certificate set $(\partial\|x^*\|_1 + \frac{1}{\alpha}x^*) \cap \mathcal{R}(A^T)$ is nonempty. Let $T_\gamma^\alpha = \frac{\alpha}{\alpha+\gamma}S_\gamma \circ (2P - I) + I - P$.

Lemma 3.1. *The set of the fixed points of T_γ^α can be described as*

$$\left\{ y^* : y^* = x^* - \gamma\eta, \eta \in \left(\partial\|x^*\|_1 + \frac{1}{\alpha}x^* \right) \cap \mathcal{R}(A^T) \right\}.$$

The proof is similar to the one of Lemma 2.2. We also have

Lemma 3.2. *For any y satisfying $\frac{\alpha}{\alpha+\gamma}R(y) \in \mathcal{Q}$ and any fixed point y^* , $T_\gamma^\alpha(y) - T_\gamma^\alpha(y^*) = [c(I_n - B^+B)(I_n - A^+A) + cB^+BA^+A + (1-c)A^+A](y - y^*)$ where $c = \frac{\alpha}{\alpha+\gamma}$.*

Proof. First, we have

$$\begin{aligned} T_\gamma^\alpha(y) &= [cS_\gamma \circ (2P - I) + I - P](y) = cS_\gamma(R(y)) + y - P(y) \\ &= c \left[R(y) - \gamma \sum_{j \in N(x^*)} e_j \operatorname{sgn}(x_j^*) - B^+BR(y) \right] + y - P(y) \end{aligned}$$

Similarly we also have

$$T_\gamma^\alpha(y^*) = c \left[R(y^*) - \gamma \sum_{j \in N(x^*)} e_j \operatorname{sgn}(x_j^*) - B^+BR(y^*) \right] + y^* - P(y^*).$$

Let $v = y - y^*$, then

$$\begin{aligned} T_\gamma^\alpha(y) - T_\gamma^\alpha(y^*) &= c [R(y) - B^+BR(y)] + y - P(y) \\ &\quad - c [R(y^*) - B^+BR(y^*)] - (y^* - P(y^*)) \\ &= c[I_n - 2A^+A - B^+B + 2B^+BA^+A]v + A^+Av \\ &= [c(I_n - B^+B)(I_n - A^+A) + cB^+BA^+A + (1-c)A^+A]v. \end{aligned}$$

□

Consider the matrix

$$\mathbf{T}(c) = c(I_n - B^+B)(I_n - A^+A) + cB^+BA^+A + (1-c)A^+A, \quad c = \frac{\alpha}{\alpha+\gamma}. \quad (3.4)$$

Then $\mathbf{T}(c) = c\mathbf{T} + (1-c)A^+A$ where $\mathbf{T} = (I_n - B^+B)(I_n - A^+A) + B^+BA^+A$.

By (2.8) and (2.9), we have

$$\mathbf{T}(c) = \tilde{B} \left(\begin{array}{ccc|c} (1-c)\sin^2\Theta + c\cos^2\Theta & (2c-1)\cos\Theta\sin\Theta & 0 & 0 \\ -\cos\Theta\sin\Theta & \cos^2\Theta & 0 & 0 \\ 0 & 0 & 0_{(r-m)} & 0 \\ \hline 0 & 0 & 0 & I_{(r+m-n)} \end{array} \right) \tilde{B}^T, \quad (3.5)$$

where $\tilde{B} = (\tilde{B}_0, \tilde{B}_1, \tilde{B}_2)$.

Following the proof in [30], it is straightforward to show there exists a dual certificate $\eta \in (\partial\|x^*\|_1 + \frac{1}{\alpha}x^*) \cap \mathcal{R}(A^T)$ such that $\mathbb{P}_{\mathcal{N}(B)}(\eta) = \mathbb{P}_{\mathcal{N}(B)}(x^*)$ and $\|\mathbb{P}_{\mathcal{R}(B^T)}(\eta)\|_\infty < 1$. So

there is at least one interior fixed point. Following Lemma 2.2, there is only one fixed point y^* if and only if $\mathcal{R}(A^T) \cap \mathcal{R}(B^T) = \{\mathbf{0}\}$.

For simplicity, we only discuss the interior fixed point case. The boundary fixed point case is similar to the previous discussion.

Assume y^k converges to an interior fixed point y^* . Let ε be the largest number such that $\mathcal{B}_\varepsilon(\mathcal{R}(y^*)) \subseteq S$. Let K be the smallest integer such that $y^K \in \mathcal{B}_\varepsilon(y^*)$ (thus $\mathcal{R}(y^K) \in \mathcal{B}_\varepsilon(\mathcal{R}(y^*))$). By nonexpansiveness of T_γ^α and \mathcal{R} , we get $\mathcal{R}(y^k) \in \mathcal{B}_\varepsilon(\mathcal{R}(y^*))$ for any $k \geq K$. So we have

$$\|y^k - y^*\| = \|\mathbf{T}(c)(y^k - y^*)\| = \dots = \|\mathbf{T}(c)^{k-K}(y^K - y^*)\| \leq \|\mathbf{T}(c)^{k-K}\| \|y^K - y^*\|, \quad \forall k > K.$$

Notice that $\mathbf{T}(c)$ is a nonnormal matrix, so $\|\mathbf{T}(c)^k\|$ is much less than $\|\mathbf{T}(c)\|^k$ for large k . Thus the asymptotic convergence rate is governed by $\lim_{k \rightarrow \infty} \sqrt[k]{\|\mathbf{T}(c)^k\|}$, which is equal to the norm of the eigenvalues of $\mathbf{T}(c)$ with the largest magnitude.

It suffices to study the matrix $\mathbf{M}(c) = \left(\begin{array}{c|c} (1-c)\sin^2\Theta + c\cos^2\Theta & (2c-1)\cos\Theta\sin\Theta \\ \hline -\cos\Theta\sin\Theta & \cos^2\Theta \end{array} \right)$ because $\mathbb{P}_{\mathcal{R}(A^T) \cap \mathcal{R}(B^T)}(y^K - y^*) = \mathbf{0}$ (otherwise y^k cannot converge to y^*).

Notice that $\det(\mathbf{M}(c) - \rho\mathbf{I}) = \prod_{i=1}^{n-r} [\rho^2 - (c\cos(2\theta_i) + 1)\rho + c\cos^2\theta_i]$. Let $\rho(\theta, c)$ denote the magnitude of the solution with the largest magnitude for the quadratic equation $\rho^2 - (c\cos(2\theta) + 1)\rho + c\cos^2\theta$, with discriminant $\Delta = \cos^2(2\theta)c^2 - 2c + 1$.

The two solutions of $\Delta = 0$ are $[1 \pm \sin(2\theta)] / \cos^2(2\theta)$. Notice that $[1 + \sin(2\theta)] / \cos^2(2\theta) \geq 1$ for $\theta \in [0, \pi/2]$ and $c \in (0, 1)$, we have

$$\rho(\theta, c) = \begin{cases} \sqrt{c} \cos \theta, & \text{if } c \geq \frac{1 - \sin(2\theta)}{\cos^2(2\theta)} = \frac{1}{(\cos\theta + \sin\theta)^2} \\ \frac{1}{2} \left(c \cos(2\theta) + 1 + \sqrt{\cos^2(2\theta)c^2 - 2c + 1} \right) & \text{if } c \leq \frac{1}{(\cos\theta + \sin\theta)^2} \end{cases}. \quad (3.6)$$

It is straightforward to check that $\rho(\theta, c)$ is monotonically decreasing with respect to θ for $\theta \in [0, \frac{\pi}{4}]$. Therefore, the asymptotic convergence rate is equal to $\rho(\theta_1, c)$ if $\theta_1 \leq \frac{\pi}{4}$.

Let $c^* = \frac{1}{(\cos\theta_1 + \sin\theta_1)^2}$ which is equal to $\arg \min_c \rho(\theta_1, c)$. Let $c^\sharp = \frac{1}{1 + 2\cos\theta_1}$ which is the solution to $\rho(\theta_1, c) = \cos\theta_1$. See Figure 1.2. Then for any $c \in (c^\sharp, 1)$, we have $\rho(\theta_1, c) < \cos\theta_1$. Namely, the asymptotic convergence rate of (3.3) is faster than (1.3) if $\frac{\alpha}{\alpha + \gamma} \in (c^\sharp, 1)$. The best asymptotic convergence rate that (3.3) can achieve is $\rho(\theta_1, c^*) = \sqrt{c^*} \cos\theta_1 = \frac{\cos\theta_1}{\cos\theta_1 + \sin\theta_1} = \frac{1}{1 + \tan\theta_1}$ when $\frac{\alpha}{\alpha + \gamma} = c^*$.

Remark 3.3. *The general cases of the two alternatives (3.1) and (3.2) with any p and q can be discussed similarly. For Douglas-Rachford splitting (1.2) using (3.1) with $q = 1$ and (3.2) with $p = 1$ or $q = 1$, the asymptotic linear rate (3.6) holds. Compared to (3.3), we observed no improvement in numerical performance by using (3.1) or (3.2) with any other values of p and q in all our numerical tests.*

3.3 Generalized Douglas-Rachford and Peaceman-Rachford splittings

For the generalized Douglas-Rachford splitting (1.5), the choice of p and q in the (3.1) and (3.2) may result in different performance. The main difference can be seen in the limiting

case $\lambda_k \equiv 2$, for which (1.5) becomes the Peaceman-Rachford splitting (1.6).

If $f(x)$ is convex and $g(x)$ is strongly convex, the convergence of (1.6) is guaranteed, see [9, 18]. On the other hand, (1.5) may not converge if $g(x)$ is only convex rather than strongly convex. For instance, (1.6) with (3.1) and $p = 1$ (or (3.2) and $q = 1$) did not converge for examples in Section 4.4. To this end, the best choices of p and q for (1.5) should be (3.1) with $q = 1$ and (3.2) with $p = 1$. We only discuss the case of using (3.1) with $q = 1$. The analysis will hold for the other one.

Let $f(x) = \|x\|_1$ and $g(x) = \iota_{\{x:Ax=b\}} + \frac{1}{2\alpha}\|x\|^2$. Consider the following generalized Douglas-Rachford splitting with a constant relaxation parameter λ :

$$\begin{cases} y^{k+1} = y^k + \lambda [S_\gamma(2x^k - y^k) - x^k] \\ x^{k+1} = \frac{\alpha}{\alpha+\gamma}y^{k+1} + A^+(b - \frac{\alpha}{\alpha+\gamma}Ay^{k+1}) \end{cases}, \quad \lambda \in (0, 2]. \quad (3.7)$$

For the algorithm (3.7), the corresponding matrix in (3.4) is

$$\mathbf{T}(c, \lambda) = I + \lambda[(I - B^+B)(2c(I - A^+A) - I) - c(I - A^+A)] = (1 - \lambda)I + \lambda[c\mathbf{T} + (1 - c)B^+B],$$

where $c = \frac{\alpha}{\alpha+\lambda}$ and $\mathbf{T} = (I - B^+B)(I - A^+A) + B^+BA^+A$.

By (2.9), we have

$$\mathbf{T}(c, \lambda) = \tilde{B} \left(\begin{array}{ccc|ccc} \lambda c \cos^2 \Theta + (1 - \lambda)I_{(n-r)} & \lambda c \cos \Theta \sin \Theta & 0 & & 0 & \\ -\lambda c \cos \Theta \sin \Theta & \lambda c \cos^2 \Theta + (1 - \lambda c)I_{(n-r)} & 0 & & 0 & \\ 0 & 0 & (1 - \lambda c)I_{(r-m)} & & 0 & \\ \hline 0 & 0 & 0 & & 0 & I_{(r+m-n)} \end{array} \right) \tilde{B}^T, \quad (3.8)$$

where $\tilde{B} = (\tilde{B}_0, \tilde{B}_1, \tilde{B}_2)$.

It suffices to study the matrix $\mathbf{M}(c, \lambda) = \left(\begin{array}{c|c} \lambda c \cos^2 \Theta + (1 - \lambda)I_{(n-r)} & \lambda c \cos \Theta \sin \Theta \\ \hline -\lambda c \cos \Theta \sin \Theta & \lambda c \cos^2 \Theta + (1 - \lambda c)I_{(n-r)} \end{array} \right)$.

Notice that $\det(\mathbf{M}(c, \lambda) - \rho I) = \prod_{i=1}^{n-r} [\rho^2 - (\lambda c \cos(2\theta_i) - \lambda + 2)\rho + c \sin^2 \theta_i \lambda^2 - (1 - c \cos(2\theta_i))\lambda + 1]$.

Let $\rho(\theta, c, \lambda)$ denote the magnitude of the solution with the largest magnitude for the quadratic equation $\rho^2 - (\lambda c \cos(2\theta) - \lambda + 2)\rho + c \sin^2 \theta \lambda^2 - (1 - c \cos(2\theta))\lambda + 1$, with discriminant $\Delta = \lambda^2(\cos^2(2\theta)c^2 - 2c + 1)$.

The two solutions of $\Delta = 0$ are $[1 \pm \sin(2\theta)] / \cos^2(2\theta)$. Notice that $[1 + \sin(2\theta)] / \cos^2(2\theta) \geq 1$ for $\theta \in [0, \pi/2]$ and $c \in (0, 1)$, we have

$$\rho(\theta, c, \lambda) = \begin{cases} \sqrt{c \sin^2 \theta \lambda^2 - (1 - c \cos(2\theta))\lambda + 1}, & \text{if } c \geq \frac{1 - \sin(2\theta)}{\cos^2(2\theta)} = \frac{1}{(\cos \theta + \sin \theta)^2} \\ \frac{1}{2} \left(\lambda c \cos(2\theta) - \lambda + 2 + \lambda \sqrt{\cos^2(2\theta)c^2 - 2c + 1} \right) & \text{if } c \leq \frac{1}{(\cos \theta + \sin \theta)^2} \end{cases}. \quad (3.9)$$

It is straightforward to check that $\rho(\theta, c, \lambda) \geq |1 - \lambda c|$ and $\rho(\theta, c, \lambda)$ is monotonically decreasing with respect to θ for $\theta \in [0, \frac{\pi}{4}]$. Therefore, the asymptotic convergence rate of (3.7) is governed by $\rho(\theta_1, c, \lambda)$ if $\theta_1 \leq \frac{\pi}{4}$.

The next step is to evaluate $\arg \min_{\lambda} \rho(\theta, c, \lambda)$. When $c \leq c^* = \frac{1}{(\cos \theta + \sin \theta)^2}$, $\rho(\theta, c, \lambda)$ is monotonically decreasing with respect to λ . Let $\bar{c} = \frac{1}{2 - \cos(2\theta)}$, for the quadratic equation

$\kappa(\lambda) = c \sin^2 \theta \lambda^2 - (1 - c \cos(2\theta))\lambda + 1$, we have

$$\arg \min_{\lambda} \kappa(\lambda) = \begin{cases} 2, & \text{if } c^* \leq c \leq \bar{c} \\ \frac{1-c \cos 2\theta}{c(1-\cos(2\theta))}, & \text{if } \bar{c} \leq c < 1 \end{cases} \quad \text{and} \quad \min \kappa(\lambda) = \begin{cases} 2c - 1, & \text{if } c^* \leq c \leq \bar{c} \\ \frac{2c-1-c^2 \cos^2 2\theta}{4c \sin^2 \theta}, & \text{if } \bar{c} \leq c < 1 \end{cases}.$$

Let $\lambda^*(\theta, c) = \arg \min_{\lambda} \rho(\theta, c, \lambda)$, then

$$\lambda^*(\theta, c) = \begin{cases} 2 & \text{if } c \leq \bar{c} = \frac{1}{2-\cos(2\theta)}, \\ \frac{\frac{1}{c}-\cos 2\theta}{1-\cos(2\theta)} & \text{if } c \geq \bar{c} \end{cases}, \quad (3.10)$$

which is a continuous non-increasing function w.r.t c and has range $(1, 2]$ for $c \in (0, 1)$.

The convergence rate with λ^* is

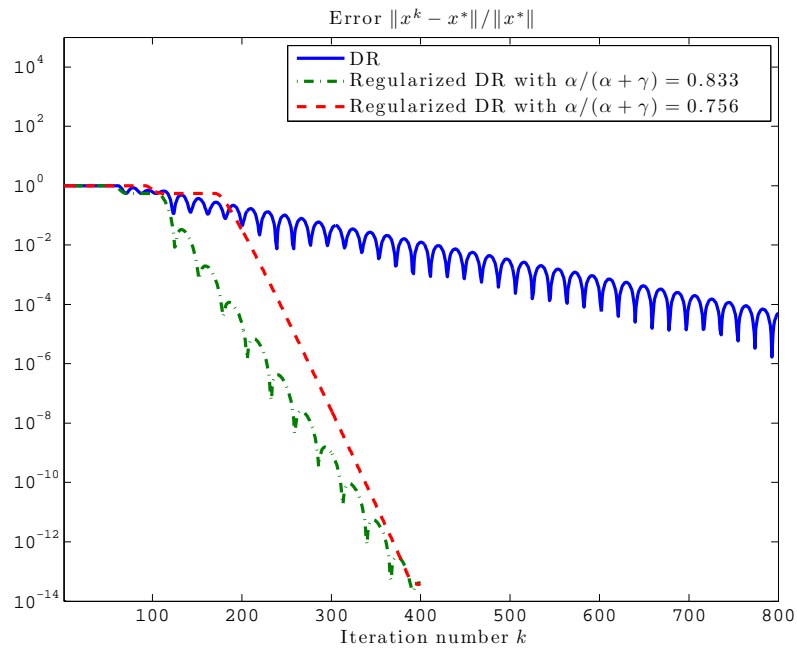
$$\rho(\theta, c, \lambda^*) = \begin{cases} \rho(\theta, c, 2) = c \cos(2\theta) + \sqrt{\cos^2(2\theta)c^2 - 2c + 1}, & \text{if } c \leq c^* = \frac{1}{(\cos \theta + \sin \theta)^2} \\ \rho(\theta, c, 2) = \sqrt{2c - 1}, & \text{if } c^* \leq c \leq \bar{c} = \frac{1}{2-\cos(2\theta)}. \\ \rho(\theta, c, \frac{1-c \cos 2\theta}{c(1-\cos 2\theta)}) = \frac{\sqrt{2c-1-c^2 \cos^2(2\theta)}}{2 \sin \theta \sqrt{c}}, & \text{if } c \geq \bar{c} \end{cases}.$$

See Figure 1.3 for the illustration of the asymptotic linear rate $\rho(\theta, c, \lambda)$.

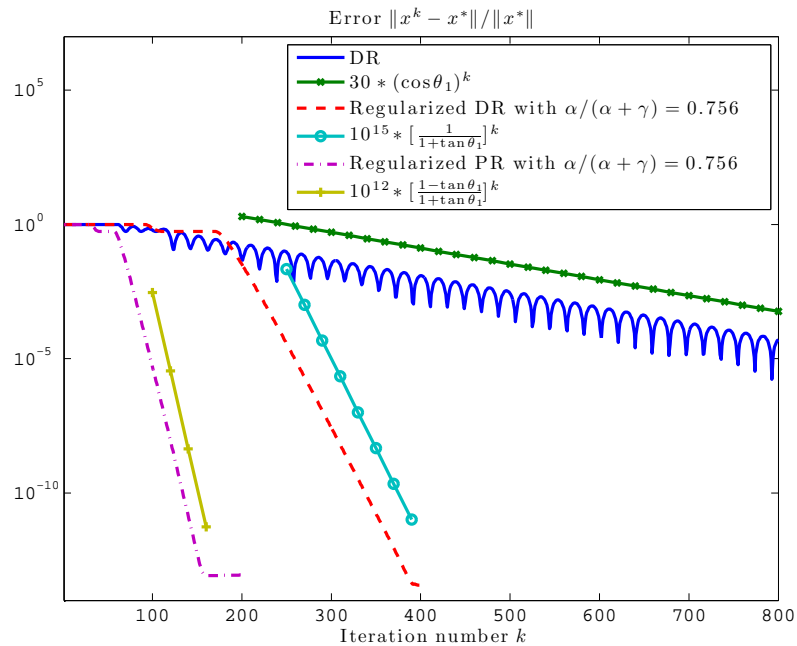
Remark 3.4. *We emphasize several interesting facts:*

- For Peaceman-Rachford splitting, i.e., (3.7) with $\lambda = 2$, if $c \geq c^*$, the asymptotic rate $\rho(\theta, c, 2) = \sqrt{2c - 1}$ is independent of θ .
- For any $c < \bar{c} = \frac{1}{2-\cos^2 \theta}$, the Peaceman-Rachford splitting is faster than Douglas-Rachford, i.e., $\rho(\theta, c, 2) < \rho(\theta, c, 1)$.
- The best possible rate of (3.7) is $\rho(\theta, c^*, 2) = \frac{1-\tan \theta}{1+\tan \theta}$.
- The quadratic function $\kappa(\lambda)$ is monotonically increasing if $\lambda \geq \frac{\frac{1}{c}-\cos 2\theta}{1-\cos(2\theta)}$ and decreasing otherwise. For any $\lambda < 1$, (3.9) and (3.10) implies $\rho(\theta, c, \lambda) > \rho(\theta, c, 1)$. Thus (3.7) with $\lambda < 1$ has slower asymptotic rate than (3.3).

Example 5 The matrix A is a 40×1000 random matrix with standard normal distribution and x^* has two nonzero components. We test the algorithms (3.3) and (3.7). See Section 4.3 for the equivalence between (3.3) and the dual split Bregman method in [27]. See Figure 3.1 for the error curve of x^k . The best choice of the parameter $c = \alpha/(\alpha + \gamma)$ according to Figure 1.2 should be $\alpha/(\alpha + \gamma) = c^*$, which is $c^* = 0.756$ for this example. Here c^* indeed gives the best asymptotic rate $\frac{1}{1+\tan \theta_1}$ for (3.3) but c^* is not necessarily the most efficient choice for a given accuracy, as we can see in the Figure 3.1 (a). The best asymptotic rates (3.3) and (3.7) are $\frac{1}{1+\tan \theta_1}$ and $\frac{1-\tan \theta_1}{1+\tan \theta_1}$ respectively when $c = c^*$ as we can see in Figure 3.1 (b).



(a) For the algorithm (3.3), $c^* = 0.756$ indeed gives the best asymptotic rate $\frac{1}{1+\tan\theta_1}$ but c^* is not necessarily the most efficient choice for a given accuracy.



(b) The best asymptotic rates.

Figure 3.1: Example 5: $\alpha = 20$ is fixed. DR stands for (1.3) and Regularized DR stands for (3.3). Regularized PR stands for (3.7) with $\lambda = 2$.

4 Dual interpretation

4.1 Chambolle and Pock's primal dual algorithm

The algorithm (1.2) is equivalent to a special case of Chambolle and Pock's primal-dual algorithm [6]. Let $w^{k+1} = (x^k - y^{k+1})/\gamma$, then (1.2) with $F = \partial f$ and $G = \partial g$ is equivalent to

$$\begin{cases} w^{k+1} &= (\mathbf{I} + \frac{1}{\gamma}\partial f^*)^{-1}(w^k + \frac{1}{\gamma}(2x^k - x^{k-1})) \\ x^{k+1} &= (\mathbf{I} + \gamma\partial g)^{-1}(x^k - \gamma w^{k+1}) \end{cases}, \quad (4.1)$$

where f^* is the conjugate function of f . Its resolvent can be evaluated by the Moreau's identity,

$$x = (\mathbf{I} + \gamma\partial f)^{-1}(x) + \gamma \left(\mathbf{I} + \frac{1}{\gamma}\partial f^* \right)^{-1} \left(\frac{x}{\gamma} \right).$$

Let $X^n = \frac{1}{n} \sum_{k=1}^n x^k$ and $W^n = \frac{1}{n} \sum_{k=1}^n w^k$, then the duality gap of the point (X^n, W^n) converges with the rate $\mathcal{O}(\frac{1}{n})$. See [6] for the proof. If $f(x) = \|x\|_1$ and $g(x) = \iota_{\{x: Ax=b\}}$, then w^k will converge to a dual certificate $\eta \in \partial\|x^*\|_1 \cap \mathcal{R}(A^T)$.

4.2 Alternating direction method of multipliers

In this subsection we recall the widely used *alternating direction method of multipliers* (ADMM), which serves as a preliminary for the next subsection. ADMM [15, 14] was shown in [13] to be equivalent to the Douglas-Rachford splitting on the dual problem. To be more specific, consider

$$\min_{z \in \mathbb{R}^m} \Psi(z) + \Phi(Dz), \quad (\text{P})$$

where Ψ and Φ are convex functions and D is a $n \times m$ matrix. The dual problem of the equivalent constrained form $\min \Psi(z) + \Phi(w)$ s.t. $Dz = w$ is

$$\min_{x \in \mathbb{R}^n} \Psi^*(-D^T x) + \Phi^*(x). \quad (\text{D})$$

By applying the Douglas-Rachford splitting (1.2) on $F = \partial[\Psi^* \circ (-D^T)]$ and $G = \partial\Phi^*$, one recovers the classical ADMM algorithm for (P),

$$\begin{cases} z^{k+1} = \arg \min_z \Psi(z) + \frac{\gamma}{2} \left\| \frac{1}{\gamma} x^k + Dz - w^k \right\|^2 \\ w^{k+1} = \arg \min_w \Phi(w) + \frac{\gamma}{2} \left\| \frac{1}{\gamma} x^k + Dz^{k+1} - w \right\|^2 \\ x^{k+1} = x^k + \gamma(Dz^{k+1} - w^{k+1}) \end{cases}, \quad (\text{ADMM})$$

with the change of variable $y^k = x^k + \gamma w^k$, and x^k unchanged.

After its discovery, ADMM has been regarded as a special augmented Lagrangian method. It turns out that ADMM can also be interpreted in the context of Bregman iterations. The split Bregman method [16] for (P) is exactly the same as (ADMM), see [26]. Since we are interested in Douglas-Rachford splitting for the primal formulation of the ℓ^1 minimization, the algorithms analyzed in the previous sections are equivalent to ADMM or split Bregman method applied to the dual formulation.

4.3 Split Bregman method on the dual problem

In this subsection we show that the analysis in Section 3 can also be applied to the split Bregman method on the dual formulation [27]. The dual problem of ℓ^2 regularized basis pursuit (1.4) can be written as

$$\min_z -b^T z + \frac{\alpha}{2} \|A^T z - \mathbb{P}_{[-1,1]^n}(A^T z)\|^2, \quad (4.2)$$

where z denotes the dual variable, see [28].

By switching the first two lines in (ADMM), we get a slightly different version of ADMM:

$$\begin{cases} w^{k+1} = \arg \min_w \Phi(w) + \frac{\gamma}{2} \|\frac{1}{\gamma} x^k + Dz^k - w\|^2 \\ z^{k+1} = \arg \min_z \Psi(z) + \frac{\gamma}{2} \|\frac{1}{\gamma} x^k + Dz - w^{k+1}\|^2 \\ x^{k+1} = x^k + \gamma(Dz^{k+1} - w^{k+1}) \end{cases} \quad (\text{ADMM2})$$

The well-known equivalence between (ADMM) and Douglas-Rachford splitting was first explained in [13]. See also [26, 11]. For completeness, we discuss the equivalence between (ADMM2) and Douglas-Rachford splitting.

Theorem 4.1. *The iterates in (ADMM2) are equivalent to the Douglas-Rachford splitting (1.2) on $F = \partial\Phi^*$ and $G = \partial[\Psi^* \circ (-D^T)]$ with $y^k = x^{k-1} - \gamma w^k$.*

Proof. For any convex function h , we have $\lambda \in \partial h(p) \iff p \in \partial h^*(\lambda)$, which implies

$$\hat{p} = \arg \min_p h(p) + \frac{\gamma}{2} \|Dp - q\|^2 \implies \gamma(D\hat{p} - q) = J_{\gamma\partial(h^* \circ (-D^T))}(-\gamma q). \quad (4.3)$$

Applying (4.3) to the first two lines of (ADMM2), we get

$$x^k - \gamma w^{k+1} = J_{\gamma F}(x^k + \gamma Dz^k) - \gamma Dz^k. \quad (4.4)$$

$$x^k + \gamma Dz^{k+1} - \gamma w^{k+1} = J_{\gamma G}(x^k - \gamma w^{k+1}). \quad (4.5)$$

Assuming $y^k = x^{k-1} - \gamma w^k$, we need to show that the $(k+1)$ -th iterate of (ADMM2) satisfies $y^{k+1} = J_{\gamma F} \circ (2J_{\gamma G} - I)y^k + (I - J_{\gamma G})y^k$ and $x^{k+1} = J_{\gamma G}(y^{k+1})$.

Notice that (4.5) implies

$$J_{\gamma G}(y^k) = J_{\gamma G}(x^{k-1} - \gamma w^k) = x^{k-1} + \gamma Dz^k - \gamma w^k.$$

So we have

$$J_{\gamma G}(y^k) - y^k = x^{k-1} + \gamma Dz^k - \gamma w^k - (x^{k-1} - \gamma w^k) = \gamma Dz^k,$$

and

$$2J_{\gamma G}(y^k) - y^k = x^{k-1} + 2\gamma Dz^k - \gamma w^k = x^{k-1} + \gamma Dz^k - \gamma w^k + \gamma Dz^k = x^k + \gamma Dz^k.$$

Thus (4.4) becomes

$$y^{k+1} = J_{\gamma F} \circ (2J_{\gamma G} - I)y^k + (I - J_{\gamma G})y^k.$$

And (4.5) is precisely $x^{k+1} = J_{\gamma G}(y^{k+1})$. □

Applying (ADMM2) on (4.2) with $\Psi(z) = -b^T z$, $\Phi(w) = \frac{\alpha}{2} \|w - \mathbb{P}_{[-1,1]^n}(w)\|^2$ and $D = A^T$, we recover the LB-SB algorithm in [27],

$$\begin{cases} w^{k+1} = \arg \min_w \frac{\alpha}{2} \|w - \mathbb{P}_{[-1,1]^n}(w)\|^2 + \frac{\gamma}{2} \|\frac{1}{\gamma} x^k + A^T z^k - w\|^2 \\ z^{k+1} = \arg \min_z -b^T z + \frac{\gamma}{2} \|\frac{1}{\gamma} x^k + A^T z - w^{k+1}\|^2 \\ x^{k+1} = x^k + \gamma(A^T z^{k+1} - w^{k+1}) \end{cases}. \quad (\text{LB-SB})$$

It is straightforward to check that $\Psi^* \circ (-A)(x) = \iota_{\{x: Ax=b\}}$ and $\Phi^*(x) = \|x\|_1 + \frac{1}{2\alpha} \|x\|^2$. By Theorem 4.1, (LB-SB) is exactly the same as (3.3). Therefore, all the results in Section 3 hold for (LB-SB). In particular, the dependence of the eventual linear convergence rate of (LB-SB) on the parameters is governed by (3.6) as illustrated in Figure 1.2.

Remark 4.2. Let z^* be the minimizer of (4.2) then $\alpha S_1(A^T z^*)$ is the solution to (1.4), see [28]. So $t^k = \alpha S_1(A^T z^k)$ can be used as the approximation to x^* , the solution to (1.4), as suggested in [27]. By Theorem 4.1, we can see that x^k will converge to x^* too. And it is easy to see that x^k satisfies the constraint $Ax^k = b$ in (3.3). But t^k does not necessarily lie in the affine set $\{x : Ax = b\}$. Thus $\{t^k\}$ and $\{x^k\}$ are two completely different sequences even though they both can be used in practice.

4.4 Practical relevance

To implement the algorithm exactly as presented earlier, the availability of A^+ is necessary. Algorithms such as (1.3) and (3.3), the same as (LB-SB), are not suitable if $(AA^T)^{-1}$ is prohibitive to obtain. On the other hand, there are quite a few important problems for which $(AA^T)^{-1}$ is cheap to compute and store in memory. For instance, AA^T may be relatively small and is a well-conditioned matrix in typical compressive sensing problems. Another example is when A^T represents a tight frame transform, for which AA^T is the identity matrix.

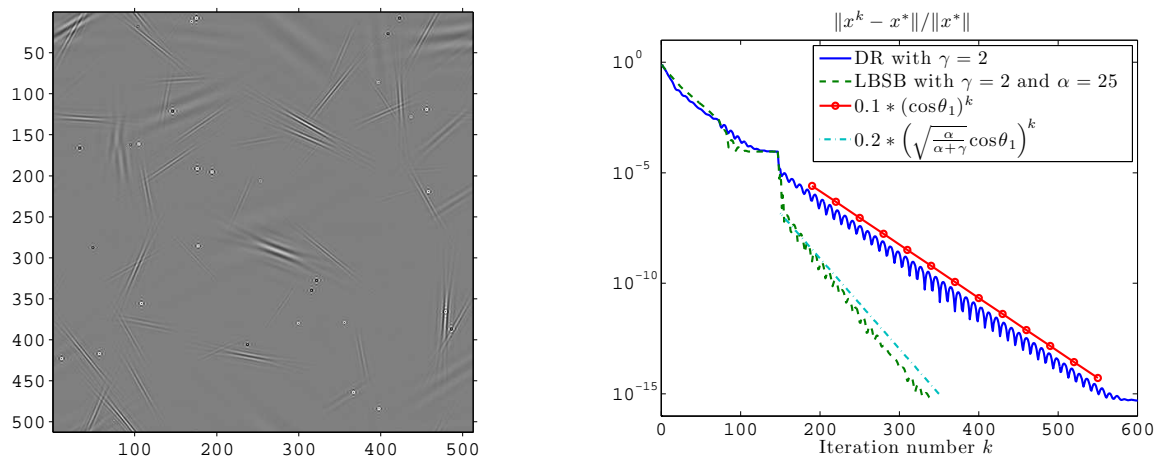
As for the efficiency of (LB-SB), see [27] for the comparison of (LB-SB) with other state-of-the-art algorithms.

Next, we discuss several examples of (3.3), (LB-SB) and (3.7) for the tight frame of discrete curvelets [4], in the scope of an application to interpolation of 2D seismic data. In the following examples, let C denote the matrix representing the wrapping version of the two-dimensional fast discrete curvelet transform [4], then C^T represents the inverse curvelet transform and $C^T C$ is the identity matrix since the curvelet transform is a tight frame.

Example 6 We construct an example with $A = C^T$ to validate formula (3.6). Consider a random sparse vector x^* with length 379831 and 93 nonzero entries, in the curvelet domain which is the range of the curvelet transform of 512×512 images. The size of the abstract matrix C^T is 262144×379831 . Notice that, for any $y \in \mathbb{R}^{512 \times 512}$, Cy is implemented through fast Fourier transform, thus the explicit matrix representation of C is never used in computation. Let $b = C^T x^*$ denote the 512×512 image generated by taking the inverse transform of x^* , see Figure 4.1 (a).

Suppose only the data b is given, to recover a sparse curvelet coefficient, we can solve (1.1) with $A = C^T$ and x being vectors in curvelet domain.

We use both (1.3) and (3.3) with $\gamma = 2$ and $\alpha = 25$ to solve (1.1). Since A is a huge implicitly defined matrix, it is not straightforward to compute the angles exactly by SVD as in small matrices examples. Instead, we obtain approximately the first principal angle $\theta_1 = \arccos(0.9459)$ between $\mathcal{N}(A)$ and $\mathcal{N}(B)$ in a more efficient ad hoc way in Appendix B. Assuming $\cos \theta_1 = 0.9459$ and $\frac{\alpha}{\alpha+\gamma} = \frac{25}{27}$, if y^k in (3.3) converged to a fixed point of the same type (interior or boundary fixed point) as y^k in (1.3), the eventual linear rate of (3.3) should be $\sqrt{\frac{\alpha}{\alpha+\gamma}} \cos \theta_1$ by (3.6). As we can see in Figure 4.1 (b), the error curve for (3.3) matched well with the eventual linear rate $\sqrt{\frac{\alpha}{\alpha+\gamma}} \cos \theta_1$.



(a) The data $b = C^T x^*$.

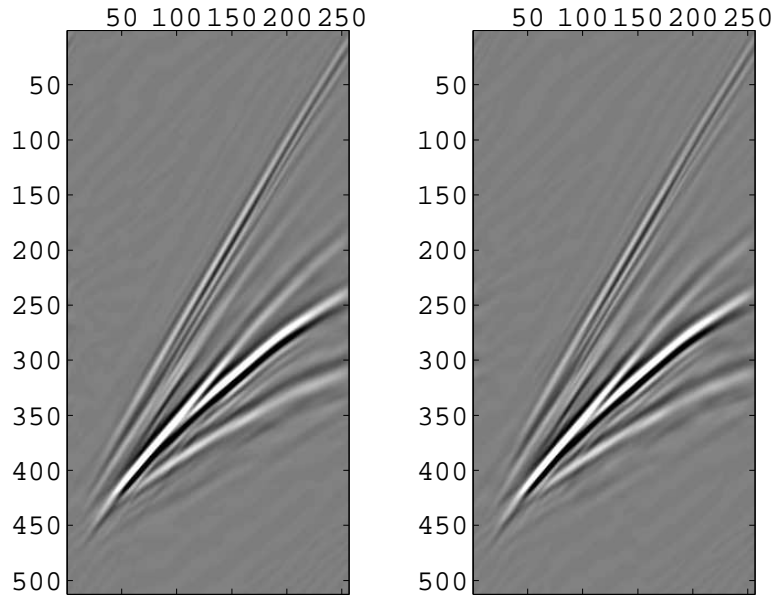
(b) Here $\cos \theta_1 = 0.9459$. DR stands for (1.3) and LBSB stands for (3.3) and (LB-SB).

Figure 4.1: Example 6: Recovery of a sparse curvelet expansion.

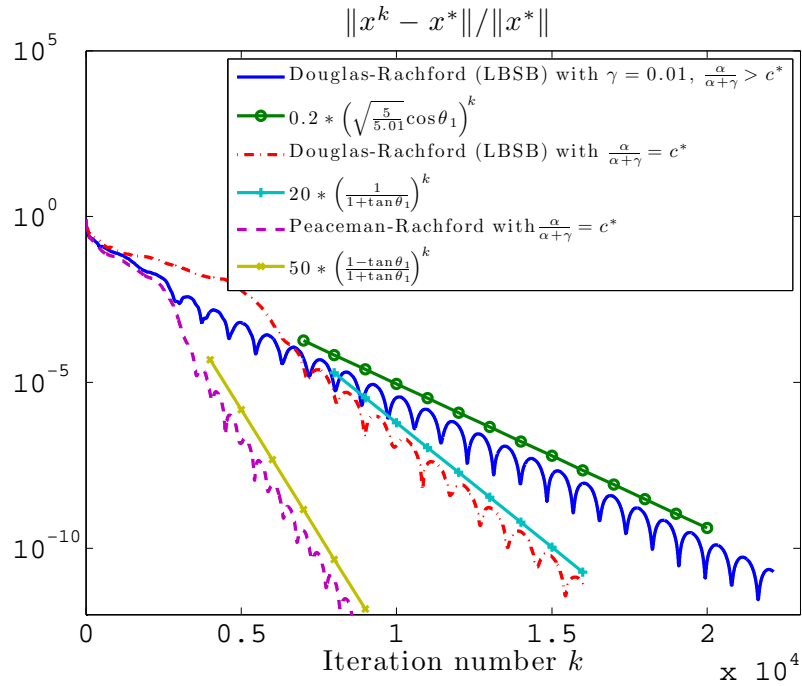
Example 7 In this example, we consider a more realistic data b as shown in the left panel of Figure 4.2 (a). The data b is generated by the following procedure. First, take a synthetic seismic dataset \tilde{b} consisting of 256 traces (columns) and 512 time samples (rows). Second, solve the basis pursuit $\min_x \|x\|_1$ with $C^T x = \tilde{b}$ by (3.3) up to 50000 iterations. Third, set the entries in x^{50000} smaller than 10^{-8} to zero and let x^* denote the resulting sparse vector, which has 679 nonzero entries. Finally, set $b = C^T x^*$.

Given only the data b , the direct curvelet transform Cb is not as sparse as x^* . Thus Cb is not the most effective choice to compress the data. To recover the curvelet coefficient sequence x^* , we alternatively solve (1.1) with $A = C^T$ and x being vectors in curvelet domain. For this particular example, x^* is recovered. By the method in Appendix B, we get $\cos \theta_1 = 0.99985$. To achieve the best asymptotic rate, the parameter ratio $\frac{\alpha}{\alpha+\gamma}$ should be $c^* = \frac{1}{(\sin \theta_1 + \cos \theta_1)^2} = 0.996549$ by (3.6). See Figure 4.2 (b) for the performance of (LB-SB) and (3.7) with fixed $\alpha = 5$ and we can see the asymptotic linear rates match the best rates $\frac{1}{1+\tan \theta_1}$ and $\frac{1-\tan \theta_1}{1+\tan \theta_1}$ when $\frac{\alpha}{\alpha+\gamma} = c^*$.

Example 8 We consider an example of seismic data interpolation via curvelets. Let b be

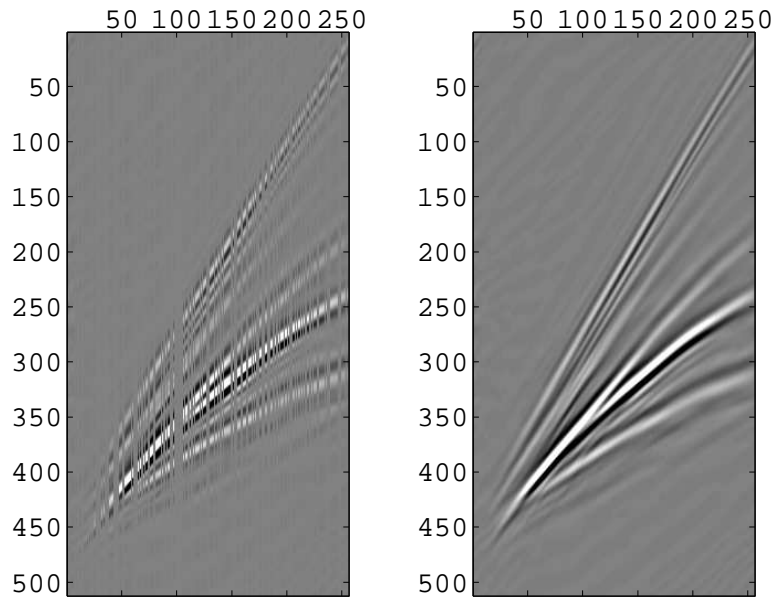


(a) Left: the original data b . Right: reconstructed data with 400 largest curvelet coefficients x^* .

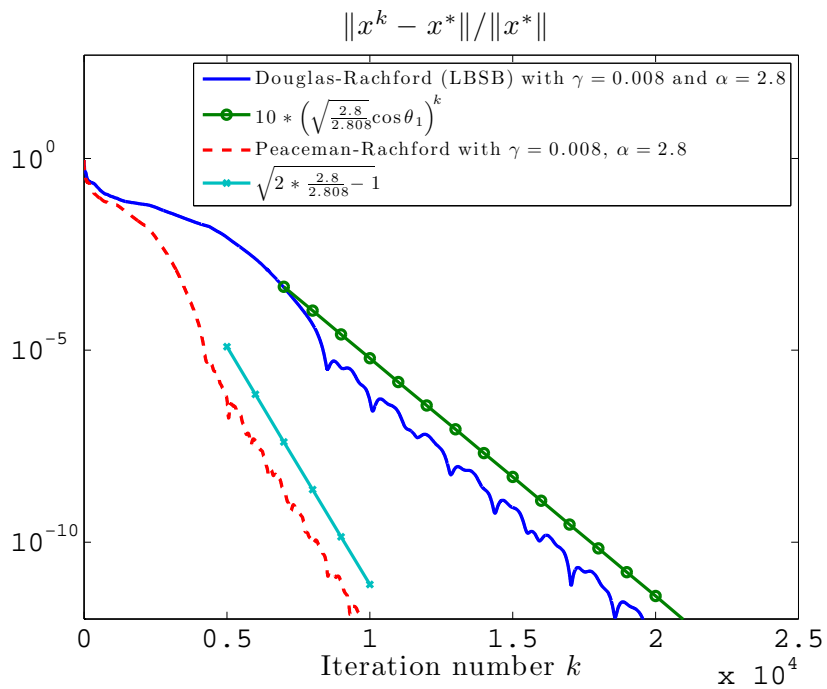


(b) $\alpha = 5$ is fixed. The eventual linear convergence. Douglas-Rachford (LBSB) stands for (3.3) and (LB-SB). Peaceman-Rachford stands for (3.7) with $\lambda = 2$.

Figure 4.2: Example 7: compression of seismic data.



(a) Left: observed data, about 47% random traces missing. Right: recovered data after 200 iterations with relative error $\|C^T x^{200} - b\|/\|b\| = 2.6\%$ where b is the original data in Figure 4.2 (a).



(b) Douglas-Rachford (LBSB) stands for (3.3) and (LB-SB). Peaceman-Rachford stands for (3.7) with $\lambda = 2$.

Figure 4.3: Example 8: seismic data interpolation.

the same data as in the previous example, see the left panel in Figure 4.2 (a). Let Ω be the sampling operator corresponding to 47 percent random traces missing, see Figure 4.3 (a).

Given the observed data $\bar{b} = \Omega(b)$, to interpolate and recover missing data (traces), one effective model is to pursue sparsity in the curvelet domain [21], i.e., solving $\min_x \|x\|_1$ with the constraint $\Omega(C^T x) = \bar{b}$. Here x is a vector of curvelet coefficients. If x^* is a minimizer, then $C^T x^*$ can be used as the recovered data. Let $Ax = \Omega(C^T x)$. Then $A^+ = A^T$ since Ω represents a sampling operator. Thus (3.3) and (LB-SB) are straightforward to implement. For this relatively ideal example, the original data b can be recovered. We also observe the eventual linear convergence. See Figure 4.3 (a) for the recovered data after 200 iterations of (3.3) and (LB-SB).

5 Conclusion

In this paper, we analyze the asymptotic convergence rate for Douglas-Rachford splitting algorithms on the primal formulation of the basis pursuit, providing a quantification of asymptotic convergence rate of such algorithms. In particular, we get the asymptotic convergence rates for ℓ^2 -regularized Douglas-Rachford, and the generalized Douglas-Rachford including the Peaceman-Rachford splitting. The explicit dependence of the convergence rate on the parameters may shed light on how to choose parameters in practice.

Appendix A

Lemma A.1. *Let T be a firmly non-expansive operator, i.e., $\|T(u) - T(v)\|^2 \leq \langle u - v, T(u) - T(v) \rangle$ for any u and v . Then the iterates $y^{k+1} = T(y^k)$ satisfy $\|y^k - y^{k+1}\|^2 \leq \frac{1}{k+1} \|y^0 - y^*\|^2$ where y^* is any fixed point of T .*

Proof. The firm non-expansiveness implies

$$\begin{aligned} \|(I - T)(u) - (I - T)(v)\|^2 &= \|u - v\|^2 + \|T(u) - T(v)\|^2 - 2\langle u - v, T(u) - T(v) \rangle \\ &\leq \|u - v\|^2 - \|T(u) - T(v)\|^2. \end{aligned}$$

Let $u = y^*$ and $v = y^k$, then

$$\|y^{k+1} - y^k\|^2 \leq \|y^k - y^*\|^2 - \|y^{k+1} - y^*\|^2.$$

Summing the inequality above, we get $\sum_{k=0}^{\infty} \|y^{k+1} - y^k\|^2 \leq \|y^0 - y^*\|^2$. By the firm non-expansiveness and the Cauchy-Schwarz inequality, we have $\|y^{k+1} - y^k\| \leq \|y^k - y^{k-1}\|$, which implies $\|y^{n+1} - y^n\|^2 \leq \frac{1}{n+1} \sum_{k=0}^n \|y^{k+1} - y^k\|^2 \leq \frac{1}{n+1} \sum_{k=0}^{\infty} \|y^{k+1} - y^k\|^2 \leq \frac{1}{n+1} \|y^0 - y^*\|^2$. \square

For the Douglas-Rachford splitting, see [20] for a different proof for this fact.

Appendix B

Suppose $\mathcal{N}(A) \cap \mathcal{N}(B) = \{\mathbf{0}\}$, we discuss an ad hoc way to find an approximation of the first principal angle θ_1 between $\mathcal{N}(A)$ and $\mathcal{N}(B)$. Define the projection operators $P_{\mathcal{N}(A)}(x) = (I - A^+A)x$ and $P_{\mathcal{N}(B)}(x) = (I - B^+B)x$. Consider finding a point in the intersections of two linear subspaces,

$$\text{find } x \in \mathcal{N}(A) \cap \mathcal{N}(B), \quad (\text{B.1})$$

by von Neumann's alternating projection algorithm,

$$x^{k+1} = P_{\mathcal{N}(A)}P_{\mathcal{N}(B)}(x^k), \quad (\text{B.2})$$

or the Douglas-Rachford splitting,

$$y^{k+1} = \frac{1}{2}[(2P_{\mathcal{N}(A)} - I)(2P_{\mathcal{N}(B)} - I) + I](y^k), \quad x^{k+1} = P_{\mathcal{N}(B)}(y^{k+1}). \quad (\text{B.3})$$

For the algorithm (B.2), we have the error estimate $\|x^k\| = \|(I - A^+A)(I - B^+B)^k x^0\| \leq (\cos \theta_1)^{2k} \|x^0\|$ by (2.7).

Assume y^* and x^* are the fixed points of the iteration (B.3). Let $\mathbf{T} = (I - A^+A)(I - B^+B) + A^+AB^+B$. For the algorithm (B.3), by (2.9), we have

$$\|x^{k+1} - x^*\| \leq \|y^{k+1} - y^*\| = \|\mathbf{T}(y^k - y^*)\| = \|\mathbf{T}^k(y^0 - y^*)\| \leq (\cos \theta_1)^k \|y^0 - y^*\|.$$

Notice that $\mathbf{0}$ is the only solution to (B.1). By fitting lines to $\log(\|x^k\|)$ for large k in (B.2) and (B.3), we get an approximation of $2 \log \cos \theta_1$ and $\log \cos \theta_1$ respectively. In practice, (B.2) is better since the rate is faster and $\|x^k\|$ is monotone in k . This could be an efficient ad hoc way to obtain θ_1 when the matrix A is implicitly defined as in the examples in Section 4.4.

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