

Denote by $\Gamma_0(\mathcal{X})$ the set of proper convex l.s.c. functions on $\mathcal{X} \rightarrow (-\infty, +\infty]$.

Douglas-Rachford algorithm

Let A and B be maximal monotone operators on $\mathcal{X} \rightarrow 2^{\mathcal{X}}$. Denote by J_A, J_B their resolvents. Define

$$C_A = 2J_A - I$$

and $C_B = 2J_B - I$. The Douglas-Rachford (DR) operator is given by

$$T = \frac{I + C_A C_B}{2}.$$

Exercise 1 (Fixed points of the DR-operator). The aim is to prove the following points.

- i)* If $\xi \in \text{fix } T$, then $J_B(\xi) \in \text{zer}(A + B)$.
- ii)* If $\text{zer}(A + B) \neq \emptyset$, then $\text{fix } T \neq \emptyset$.

1. Show that $\text{fix } T = \text{fix } C_A C_B$.
2. Choose $\xi \in \mathcal{X}$. Define $u = J_B(\xi)$, $b = \xi - u$. Prove that

$$C_B(\xi) = u - b.$$

3. Assume that $\xi \in \text{fix } C_A C_B$. Prove that $u = J_A(u - b)$.
4. Deduce that $0 \in b + A(u)$.
5. Using that $J_B(\xi) = u$, show that $b \in B(u)$.
6. Deduce that $u \in \text{zer}(A + B)$ and conclude about point *i*).
7. Consider an arbitrary $\bar{u} \in \text{zer}(A + B)$. Prove that $\exists \bar{b} \in B(\bar{u})$ s.t. $-\bar{b} \in A(\bar{u})$.
8. Using that $\bar{b} \in B(\bar{u})$, prove that $\bar{u} = J_B(\bar{u} + \bar{b})$. Deduce that $C_B(\bar{u} + \bar{b}) = \bar{u} - \bar{b}$.
9. Using that $-\bar{b} \in A(\bar{u})$, prove that $\bar{u} = J_A(\bar{u} - \bar{b})$. Deduce that $C_A(\bar{u} - \bar{b}) = \bar{u} + \bar{b}$.
10. From the previous two questions, deduce that $\bar{u} + \bar{b} \in \text{fix } C_A C_B$ and conclude.

Exercise 2 (DR as an averaged operator). The aim is to prove the following result.

$$T = \frac{I + C_A C_B}{2} \text{ is an averaged operator.}$$

We recall the inequality: $\|J_B(x) - J_B(y)\|^2 \leq \|x - y\|^2 - \|(I - J_B)(x) - (I - J_B)(y)\|^2$.

1. Using the above inequality, prove that C_B is non-expansive i.e., $\|C_Bx - C_By\| \leq \|x - y\|$ for every x, y .
2. Show that C_AC_B is non-expansive.
3. Prove that $\|Tx - Ty\|^2 \leq \|x - y\|^2 - \|(I - T)(x) - (I - T)(y)\|^2$ and conclude.
Hint: Use the parallelogram identity $2\|a\|^2 + 2\|b\|^2 = \|a + b\|^2 + \|a - b\|^2$ with $a = Tx - Ty$ and $b = (I - T)(x) - (I - T)(y)$, along with question 2.

Exercise 3. We assume that $\text{zer}(A + B) \neq \emptyset$. We consider the iterates $\xi^{k+1} = T(\xi^k)$.

1. Show that the iterates ξ^k are generated by the following algorithm:

$$\begin{aligned} u^k &= J_B(\xi^k) \\ v^k &= J_A(2u^k - \xi^k) \\ \xi^{k+1} &= \xi^k + v^k - u^k. \end{aligned}$$

2. Prove that the above sequence (u^k) converges to a point in $\text{zer}(A + B)$.
3. Consider the problem

$$\text{minimize } f + g$$
 where $f, g \in \Gamma_0(\mathcal{X})$. Let $\gamma > 0$. Using Question 2, propose an algorithm which requires one call to $\text{prox}_{\gamma f}$ and $\text{prox}_{\gamma g}$ at every iteration.
4. Under what sufficient condition on $f + g$ does this algorithm indeed converge to a minimizer?

Exercise 4 (Parallel programming). Consider the problem

$$\text{minimize } \sum_{i=1}^n f_i(x) \text{ w.r.t. } x \in \mathcal{X} \tag{1}$$

where $f_1, \dots, f_n \in \Gamma_0(\mathcal{X})$. Let $C \subset \mathcal{X}^n$ be the linear space $C := \{(x, \dots, x) : x \in \mathcal{X}\}$.

1. In what sense is the following problem equivalent to (1) ?

$$\text{minimize } \sum_{i=1}^n f_i(x_i) + \iota_C(x_1, \dots, x_n) \text{ w.r.t. } (x_1, \dots, x_n) \in \mathcal{X}^n$$

2. Write the Douglas-Rachford algorithm associated to this problem.
3. In what sense does this algorithm deserves the name of *parallel algorithm*?

Smoothness, strong convexity and Baillon Haddad's lemma

- We say that $f : \mathcal{X} \rightarrow \mathbb{R}$ is L -smooth if it is differentiable and if ∇f is L -lipschitz continuous.
- We say that $f \in \Gamma_0(\mathcal{X})$ is μ -strongly convex ($\mu > 0$) if $f - \frac{\mu}{2} \|\cdot\|^2$ is convex.
- We say that a operator $A : \mathcal{X} \rightarrow 2^{\mathcal{X}}$ is μ -strongly monotone if

$$\forall (x, y) \in \text{dom}(A) \times \text{dom}(A), \forall (u, v) \in A(x) \times A(y), \langle u - v, x - y \rangle \geq \mu \|x - y\|^2.$$

Exercise 5. The aim is to prove the statement:

If $f \in \Gamma_0(\mathcal{X})$ is μ -strongly convex, then f^* is μ^{-1} -smooth.

1. Let $f \in \Gamma_0(\mathcal{X})$ be μ -strongly convex. Prove that ∂f is μ -strongly monotone.
Hint: set $g := f - \frac{\mu}{2} \|\cdot\|^2$ and use that ∂g is monotone.
2. Justify that $\text{dom}(f^*) = \mathcal{X}$.
3. Show that for all $\varphi \in \mathcal{X}$, $\partial f^*(\varphi) = \arg \min_{x \in \mathcal{X}} f(x) - \langle \varphi, x \rangle$.
4. Deduce that f^* is differentiable.
5. Using 1), prove that for every $\varphi, \lambda \in \mathcal{X}$,

$$\langle \varphi - \lambda, \nabla f^*(\varphi) - \nabla f^*(\lambda) \rangle \geq \mu \|\nabla f^*(\varphi) - \nabla f^*(\lambda)\|^2. \quad (2)$$

6. Conclude.

As a matter of fact, the above result has a converse, which we admit (the proof can be found in Hiriart-Urruty and LeMaréchal, Fundamentals of Convex Analysis.).

If f is convex and L -smooth, then f^* is L^{-1} -strongly convex

7. Using Question 5, recover the Baillon-Haddad Lemma.

Correction 1

1. *Evident.*
2. $C_B(\xi) = 2u - (u + b) = u - b$.
3. If $\xi = C_A C_B(\xi)$, then $\xi = C_A(u - b)$. This reads $u + b = 2J_A(u - b) - u + b$. Thus, $u = J_A(u - b)$.
4. Consequently, $u - b \in (I + A)(u)$, which reads $-b \in A(u)$.
5. As $J_B(\xi) = u$, we have $\xi \in u + B(u)$, thus $b = \xi - u \in B(u)$.
6. Given $\xi \in \text{fix } T$, we have found some $b \in B(u)$ s.t. $0 \in b + A(u)$. That is, $0 \in B(u) + A(u)$. Thus, $u \in \text{zer}(A + B)$.
7. Evident from the definition of $\text{zer}(A + B)$.
8. One has $\bar{b} \in B(\bar{u})$, thus $\bar{u} + \bar{b} \in (I + B)(\bar{u})$, hence $\bar{u} = J_A(\bar{u} + \bar{b})$. Thus $C_A(\bar{u} + \bar{b}) = 2\bar{u} - (\bar{u} + \bar{b}) = \bar{u} - \bar{b}$.
9. One has $-\bar{b} \in A(\bar{u})$, thus $\bar{u} - \bar{b} \in (I + A)(\bar{u})$, hence $\bar{u} = J_A(\bar{u} - \bar{b})$. Thus $C_A(\bar{u} - \bar{b}) = 2\bar{u} - (\bar{u} - \bar{b}) = \bar{u} + \bar{b}$.
10. One has $\bar{u} + \bar{b} = C_A(\bar{u} - \bar{b}) = C_A C_B(\bar{u} + \bar{b})$.

Correction 2

1. Set $C = C_B$. As $J_B = \frac{I+C}{2}$, the inequality given in the text reads:

$$\left\| \frac{x - y + Cx - Cy}{2} \right\|^2 \leq \|x - y\|^2 - \left\| \frac{x - y - (Cx - Cy)}{2} \right\|^2.$$

The result follows by simply expanding the squared-norms in both handsides of the above inequality.

2. Straightforward by composition of two non-expansive mappings.
3. Setting a and b as suggested, we obtain $a + b = x - y$ and

$$a - b = (2T - I)(x) - (2T - I)(y) = C_A C_B x - C_A C_B y.$$

In particular $\|a - b\| \leq \|x - y\|$. The parallelogram identity yields

$$2\|Tx - Ty\|^2 + 2\|(I - T)(x) - (I - T)(y)\|^2 \leq 2\|x - y\|^2,$$

which is the expected result.

Correction 3

1. Just expand T as a function of J_A, J_B .
2. As $\text{zer}(A+B) \neq \emptyset$, we have $\text{fix} T \neq \emptyset$ (see exercise 1). As T is averaged, ξ^k converges to a point ξ^* in $\text{fix} T$. By continuity of J_B , u^k converges to $J_B(\xi^*)$. By exercise 1, $J_B(\xi^*) \in \text{zer}(A+B)$.
3. Just replace J_A, J_B by $\text{prox}_{\gamma f}$ and $\text{prox}_{\gamma g}$ respectively.
4. A sufficient condition is

$$\begin{aligned} \arg \min f + g &\neq \emptyset \\ 0 &\in \text{ri}(\text{dom } f - \text{dom } g) , \end{aligned}$$

where the last condition ensures that $\arg \min f + g = \text{zer}(\partial f + \partial g)$.

Correction 4

1. If x is a feasible point for (1), then $(x, \dots, x) \in \mathcal{X}^n$ is a feasible point for the constrained problem and its objective value is $\sum_{i=1}^n f_i(x) + \iota_C(x, \dots, x) = \sum_{i=1}^n f_i(x)$.

Reciprocally, if (x_1, \dots, x_n) is a feasible point for the constrained problem, then $x_i = x_1$ for all i and x_1 is a feasible point for (1). Moreover, its objective value is $\sum_{i=1}^n f_i(x_1) = \sum_{i=1}^n f_i(x_i) + \iota_C(x_1, \dots, x_n)$.

Hence, there is a bijection between the sets of feasible points of both problems that keeps the objective value unchanged. In that sense, both problems are equivalent.

2. We choose $B = \partial \iota_C$ and $A = \partial f_1 \times \dots \times \partial f_n$.

As f is separable, $(J_A(x))_i = (\text{prox}_{f_i}(x))_i = \text{prox}_{f_i}(x_i)$.

$J_B(y) = \text{prox}_{\iota_C}(y) = \arg \min_{x \in C} \frac{1}{2} \|y - x\|^2$ so prox_{ι_C} is the projection on C . This projection amounts to computing for all i , $p_i = \frac{1}{n} \sum_{j=1}^n y_j$ and $\text{prox}_{\iota_C}(y) = p$.

Hence, the Douglas-Rachford algorithm writes

$$\begin{aligned} \forall i, u_i^k &= \frac{1}{n} \sum_{j=1}^n \xi_j^k \\ \forall i, v_i^k &= \text{prox}_{f_i}(2u_i^k - \xi_i^k) \\ \forall i, \xi_i^{k+1} &= \xi_i^k + v_i^k - u_i^k \end{aligned}$$

3. The updates for u^k amounts to a sum over n vectors. The sum is commutative and associative so this operation can be performed in parallel.

The updates for v^k and ξ^{k+1} are independent component-wise. Hence, these updates can be performed in parallel, each i being allocated to a single computing unit.

All the operations of the algorithm can be performed in parallel, so one can say that this is a parallel algorithm.

Correction 5

1. Let $g := f - \frac{\mu}{2} \|\cdot\|^2$. One has $g \in \Gamma_0(\mathcal{X})$. Thus,

$$\partial f = \partial(g + \frac{\mu}{2} \|\cdot\|^2) = \partial g + \mu I.$$

Let $(x, y) \in \text{dom}(\partial f) \times \text{dom}(\partial f)$ and choose $(u, v) \in \partial f(x) \times \partial f(y)$. One has $u - \mu x \in \partial g(x)$ and $v - \mu y \in \partial g(y)$. Thus, $\langle u - \mu x - (v - \mu y), x - y \rangle \geq 0$, which is the required inequality.

2. $f^*(\varphi) = -\inf_x (f(x) - \langle \varphi, x \rangle)$. The infimum is attained as f is strongly convex. Thus, $f^*(\varphi) = \langle \varphi, x \rangle - f(x)$ for some fixed x . Hence, $f^*(\varphi) < +\infty$. As this holds for every $\varphi \in \mathcal{X}$, we deduce that $\text{dom}(f^*) = \mathcal{X}$.
3. $x \in \partial f^*(\varphi) \Leftrightarrow \varphi \in \partial f(x) \Leftrightarrow 0 \in \partial f(x) - \varphi$. By Fermat's rule, this is equivalent to $x \in \arg \min_{y \in \mathcal{X}} f(y) - \langle \varphi, y \rangle$.
4. As f is strongly convex, the argument of the minimum is attained (for any $\varphi \in \mathcal{X}$) and is a singleton. Thus ∂f^* is single-valued, meaning that f^* is differentiable.
5. Choose $(\varphi, \lambda) \in \mathcal{X} \times \mathcal{X}$. One has $\varphi \in \partial f(\nabla f^*(\varphi))$ and similarly for λ . By strong-monotonicity of ∂f , Eq. (2) is proven.
6. The conclusion follows from Cauchy-Schwartz inequality.
7. Choose $f : \mathcal{X} \rightarrow \mathbb{R}$ as convex and L -smooth. As f^* is L^{-1} -strongly convex, Question 5 states that for every $(x, y) \in \mathcal{X} \times \mathcal{X}$,

$$\langle x - y, \nabla f^{**}(x) - \nabla f^{**}(y) \rangle \geq L^{-1} \|\nabla f^{**}(x) - \nabla f^{**}(y)\|^2.$$

As $f = f^{**}$, we obtain Baillon-Haddad's lemma.