



# Douglas–Rachford algorithm

The (Parallel) Douglas–Rachford ((P)DR) Algorithm was generalized to Hadamard manifolds in [BPS16].

The aim is to minimize the sum

$$F(p) = f(p) + g(p)$$

on a manifold, where the two summands have proximal maps  $\text{prox}_{\lambda f}$ ,  $\text{prox}_{\lambda g}$  that are easy to evaluate (maybe in closed form, or not too costly to approximate). Further, define the reflection operator at the proximal map as

$$\text{refl}_{\lambda f}(p) = \text{retr}_{\text{prox}_{\lambda f}(p)}(-\text{retr}_{\text{prox}_{\lambda f}(p)}^{-1} p).$$

Let  $\alpha_k \in [0, 1]$  with  $\sum_{k \in \mathbb{N}} \alpha_k(1 - \alpha_k) = \infty$  and  $\lambda > 0$  (which might depend on iteration  $k$  as well) be given.

Then the (P)DRA algorithm for initial data  $x_0 \in \mathcal{H}$  as

## Initialization

Initialize  $q_0 = p_0$  and  $k = 0$

## Iteration

Repeat until a convergence criterion is reached

1. Compute  $s_k = \text{refl}_{\lambda f} \text{refl}_{\lambda g}(q_k)$
2. Within that operation, store  $p_{k+1} = \text{prox}_{\lambda g}(t_k)$  which is the prox the inner reflection reflects at.
3. Compute  $q_{k+1} = g(\alpha_k; q_k, s)$ , where  $g$  is a curve approximating the shortest geodesic, provided by a retraction and its inverse
4. Set  $k = k + 1$

until a stopping criterion is met.

# Acceleration and Inertia

Before computing the first step, one can apply *inertia*: Given some  $\theta_k \in (0, 1)$  we can perform a step before, namely

$$t = \text{retr}_{q_k} \left( -\theta_k \text{retr}_{q_k}^{-1}(q_{k-1}) \right),$$

that is adding inertia from the last two results computed in step 3 and use  $t_k$  as the argument of the double-reflection in step 1.

Instead of just computing step 4, one can also add an acceleration. Let  $T$  denote the double-reflection from the first step. Then, given a number  $n$  called *acceleration* step 3 is replaced with

$$q_{k+1} = T^n(g(\alpha_k; q_k, s))$$

These both methods can also be combined by specifying inertia and acceleration

## Result

The result is given by the last computed  $p_K$ .

For the parallel version, the first proximal map is a vectorial version where in each component one prox is applied to the corresponding copy of  $t_k$  and the second proximal map corresponds to the indicator function of the set, where all copies are equal (in  $\mathcal{H}^n$ , where  $n$  is the number of copies), leading to the second prox being the Riemannian mean.

## Interface

### ✓ `Manopt.DouglasRachford` — Function

```
DouglasRachford(M, f, proxes_f, p)
DouglasRachford(M, mpo, p)
```

Compute the Douglas-Rachford algorithm on the manifold  $\mathcal{M}$ , initial data  $p$  and the (two) proximal maps `proxMaps`, see [Bergmann, Persch, Steidl, SIAM J Imag Sci, 2016](#).

For  $k > 2$  proximal maps, the problem is reformulated using the parallel Douglas Rachford: A vectorial proximal map on the power manifold  $\mathcal{M}^k$  is introduced as the first proximal map and the second proximal map of the is set to the mean (Riemannian Center of mass). This hence also boils down to two proximal maps, though each evaluates proximal maps in parallel, i.e.

component wise in a vector.

If you provide a [ManifoldProximalMapObjective](#) mpo instead, the proximal maps are kept unchanged.

## Input

- $M$  – a Riemannian Manifold  $\mathcal{M}$
- $F$  – a cost function consisting of a sum of cost functions
- `proxes_f` – functions of the form  $(M, \lambda, p) \rightarrow \dots$  performing a proximal maps, where  $\lambda$  denotes the proximal parameter, for each of the summands of  $F$ . These can also be given in the [InplaceEvaluation](#) variants  $(M, q, \lambda, p) \rightarrow \dots$  computing in place of  $q$ .
- $p$  – initial data  $p \in \mathcal{M}$

## Optional values

- $\lambda - (i \rightarrow 1.0)$  function to provide the value for the proximal  $\lambda_i$  parameter during the calls
- $\alpha - (i \rightarrow 0.9)$  relaxation parameter  $\alpha_i$  of the step from old to new iterate,  $q^{(k+1)} = g(\alpha(k); q^{(k)}, s^{(k)})$ , where  $s^{(k)}$  is the result of the double
- $\theta - (\text{Nothing})$  function  $(i \rightarrow 0.0)$  to provide inertia  $\theta_i$ . `Nothing` deactivates this and is equivalent to always returning 0.
- `inverse_retraction_method` – an inverse retraction method
- $n$  –  $n$ -acceleration, apply the double reflection (T)  $n$  times after relaxation
- $R - (\text{reflect or reflect!})$  method employed in the iteration to perform the reflection of  $x$  at the prox  $p$ .
- `reflection_evaluation - (AllocatingEvaluation ())` specify whether the reflection works inplace or allocating (default)

whether  $R$  works inplace or allocating

- `retraction_method` – a retraction method
- `stop - (StopAfterIteration (300))` a [StoppingCriterion](#)
- `parallel - (false)` indicate whether we are running a parallel Douglas-Rachford or not.
- $X - (\text{zero\_vector}(M, p))$  a temporary storage for a tangent vector

and the ones that are passed to [decorate\\_state!](#) for decorators.

## Output

the obtained (approximate) minimizer  $p^*$ , see [get\\_solver\\_return](#) for details

## ✓ [Manopt.DouglasRachford!](#) – Function

```
DouglasRachford!(M, f, proxes_f, p)
DouglasRachford!(M, mpo, p)
```

Compute the Douglas-Rachford algorithm on the manifold  $\mathcal{M}$ , initial data  $p \in \mathcal{M}$  and the (two) proximal maps `proxes_f` in place of `p`.

For  $k > 2$  proximal maps, the problem is reformulated using the parallel Douglas Rachford: A vectorial proximal map on the power manifold  $\mathcal{M}^k$  is introduced as the first proximal map and the second proximal map of the is set to the mean (Riemannian Center of mass). This hence also boils down to two proximal maps, though each evaluates proximal maps in parallel, i.e. component wise in a vector.

### ! Note

While creating the new staring point  $p'$  on the power manifold, a copy of  $p$  is created, so that the (by  $k > 2$  implicitly generated) parallel Douglas Rachford does not work in-place for now.

If you provide a [ManifoldProximalMapObjective](#) `mpo` instead, the proximal maps are kept unchanged.

### Input

- $M$  – a Riemannian Manifold  $\mathcal{M}$
- $f$  – a cost function consisting of a sum of cost functions
- `proxes_f` – functions of the form  $(M, \lambda, p) \rightarrow q$  or  $(M, q, \lambda, p) \rightarrow q$  performing a proximal map, where  $\lambda$  denotes the proximal parameter, for each of the summands of  $f$ .
- $p$  – initial point  $p \in \mathcal{M}$

For more options, see [DouglasRachford](#).

## State

## ✓ [Manopt.DouglasRachfordState](#) – Type

```
DouglasRachfordState <: AbstractManoptSolverState
```

Store all options required for the DouglasRachford algorithm,

## Fields

- $p$  - the current iterate (result) For the (parallel) Douglas-Rachford. This is the “shadow sequence”, the proximal map of the first prox. For the parallel DR, this is a single point, not a point on the power manifold.
- $q$  - (internal) the last result of the double reflection at the proxes relaxed. This is the variable converging to the fix point. Inertia and acceleration apply to this iterate.
- $q\_old, q\_tmp, p\_base$  - (internal) a temporary storage used within the double reflection or inertia.
- $\lambda$  - (i-> 1.0) function to provide the value for the proximal  $\lambda_i$  parameter during the calls
- $\alpha$  - (i-> 0.9) relaxation parameter  $\alpha_i$  of the step from old to new iterate,  $q^{(k+1)} = g(\alpha(k); q^{(k)}, s^{(k)})$ , where  $s^{(k)}$  is the result of the double
- $\theta$  - (Nothing) function (i->0.0) to provide inertia  $\theta_i$ . Nothing deactivates this and is equivalent to always returning 0.
- `inverse_retraction_method` - an inverse retraction method
- $n$  -  $n$ -acceleration, apply the double reflection (T)  $n$  times after relaxation
- $R$  - (`reflect` or `reflect!`) method employed in the iteration to perform the reflection of  $x$  at the prox  $p$ .
- `reflection_evaluation` - (`AllocatingEvaluation()`) specify whether the reflection works inplace or allocating (default)

whether  $R$  works inplace or allocating

- `retraction_method` - a retraction method
- `stop` - (`StopAfterIteration(300)`) a `StoppingCriterion`
- `parallel` - (false) indicate whether we are running a parallel Douglas-Rachford or not.
- $X$  - (`zero_vector(M, p)`) a temporary storage for a tangent vector

## Constructor

```
DouglasRachfordState(M, p; kwargs...)
```



Generate the options for a Manifold  $M$  and an initial point  $p$ , where all fields with defaults above can be passed as keyword arguments.

For specific `DebugActions` and `RecordActions` see also `Cyclic Proximal Point`.

Furthermore, this solver has a short hand notation for the involved `reflect`ion.

## ✓ `Manopt.reflect` — Function

```
reflect(M, f, x; kwargs...)
reflect!(M, q, f, x; kwargs...)
```

reflect the point  $x$  from the manifold  $M$  at the point  $f(x)$  of the function  $f : \mathcal{M} \rightarrow \mathcal{M}$ , i.e.,

$$\text{refl}_f(x) = \text{refl}_{f(x)}(x),$$

Compute the result in  $q$ .

see also `reflect(M, p, x)`, to which the keywords are also passed to.

```
reflect(M, p, x, kwargs...)
reflect!(M, q, p, x, kwargs...)
```

Reflect the point  $x$  from the manifold  $M$  at point  $p$ , i.e.

$$\text{refl}_p(x) = \text{retr}_p(-\text{retr}_p^{-1} x).$$

where  $\text{retr}$  and  $\text{retr}^{-1}$  denote a retraction and an inverse retraction, respectively. This can also be done in place of  $q$ .

### Keyword arguments

- `retraction_method` (`default_retraction_method(M, typeof(p))`) the retraction to use in the reflection
- `inverse_retraction_method` (`default_inverse_retraction_method(M, typeof(p))`) the inverse retraction to use within the reflection

and for the `reflect!` additionally

- `X` (`zero_vector(M, p)`) a temporary memory to compute the inverse retraction in place. otherwise this is the memory that would be allocated anyways.

Passing `X` to `reflect` will just have no effect.

## Technical details

The `DouglasRachford` solver requires the following functions of a manifold to be available

- A `retract!` ( $M$ ,  $q$ ,  $p$ ,  $X$ ); it is recommended to set the `default_retraction_method` to a favourite retraction. If this default is set, a `retraction_method=` does not have to be specified.
- An `inverse_retract!` ( $M$ ,  $X$ ,  $p$ ,  $q$ ); it is recommended to set the `default_inverse_retraction_method` to a favourite retraction. If this default is set, a `inverse_retraction_method=` does not have to be specified.
- A `copyto!` ( $M$ ,  $q$ ,  $p$ ) and `copy` ( $M, p$ ) for points.

By default, one of the stopping criteria is `StopWhenChangeLess`, which requires

- An `inverse_retract!` ( $M$ ,  $X$ ,  $p$ ,  $q$ ); it is recommended to set the `default_inverse_retraction_method` to a favourite retraction. If this default is set, a `inverse_retraction_method=` or `inverse_retraction_method_dual=` (for  $\mathcal{N}$ ) does not have to be specified or the `distance` ( $M$ ,  $p$ ,  $q$ ) for said default inverse retraction.

## Literature

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« [Difference of Convex](#)

[Exact Penalty Method](#) »

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