






# Total variation regularization for X-ray tomography

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Some helpful resources on the Chambolle–Pock algorithm:

-  A. Chambolle and T. Pock. A first-order primal-dual algorithm for convex problems with applications to imaging. *J. Math. Imaging Vision* **40**:120-145, 2011.
-  L. Condat. A generic proximal algorithm for convex optimization – application to total variation minimization. *IEEE Signal Proc. Letters* **21**(8):985–989, 2014.
-  E. Y. Sidky, J. H. Jørgensen, and X. Pan. Convex optimization problem prototyping for image reconstruction in computed tomography with the Chambolle-Pock algorithm. *Phys. Med. Biol.* **57**:3065–3091, 2012.
-  Operator Discretization Library. [https://odl.readthedocs.io/math/solvers/nonsmooth/chambolle\\_pock.html](https://odl.readthedocs.io/math/solvers/nonsmooth/chambolle_pock.html), 2017.
-  PORTAL. <https://portal.readthedocs.io/en/latest/chambollepock.html>, written by P. Paleo, 2015.

Additional resources on total variation regularization for X-ray tomography:

-  J. L. Mueller and S. Siltanen. Linear and Nonlinear Inverse Problems with Practical Applications. 2012.
-  S. Siltanen. Total variation regularization for X-ray tomography. FIPS Computational Blog, <https://blog.fips.fi/tomography/x-ray/total-variation-regularization-for-x-ray-tomography/>, 2017.

Recall that the discrete measurement model for X-ray tomography can be expressed as

$$y = Ax.$$

This time, we consider solving the inverse problem of recovering  $x$  based on noisy measurements  $y$ .

We are interested in *anisotropic total variation regularization*

$$\arg \min_{x \geq 0} \left\{ \frac{1}{2} \|y - Ax\|^2 + \lambda \|Dx\|_1 \right\}, \quad \lambda > 0,$$

where  $\|x\|_1 = \sum_i |x_i|$ ,  $D = \begin{bmatrix} L_H \\ L_V \end{bmatrix}$  is the discretized (image) gradient operator,

$$\|Dx\|_1 = \sum_j |(Dx)_j| = \sum_j |(L_H x)_j| + \sum_j |(L_V x)_j|,$$

and  $L_H$  and  $L_V$  denote the horizontal and vertical (image) finite difference matrices, respectively.

Special feature: TV regularization preserves sharp edges.

$x_{91}$	$x_{92}$	$x_{93}$	$x_{94}$	$x_{95}$	$x_{96}$	$x_{97}$	$x_{98}$	$x_{99}$	$x_{100}$
$x_{81}$	$x_{82}$	$x_{83}$	$x_{84}$	$x_{85}$	$x_{86}$	$x_{87}$	$x_{88}$	$x_{89}$	$x_{90}$
$x_{71}$	$x_{72}$	$x_{73}$	$x_{74}$	$x_{75}$	$x_{76}$	$x_{77}$	$x_{78}$	$x_{79}$	$x_{80}$
$x_{61}$	$x_{62}$	$x_{63}$	$x_{64}$	$x_{65}$	$x_{66}$	$x_{67}$	$x_{68}$	$x_{69}$	$x_{70}$
$x_{51}$	$x_{52}$	$x_{53}$	$x_{54}$	$x_{55}$	$x_{56}$	$x_{57}$	$x_{58}$	$x_{59}$	$x_{60}$
$x_{41}$	$x_{42}$	$x_{43}$	$x_{44}$	$x_{45}$	$x_{46}$	$x_{47}$	$x_{48}$	$x_{49}$	$x_{50}$
$x_{31}$	$x_{32}$	$x_{33}$	$x_{34}$	$x_{35}$	$x_{36}$	$x_{37}$	$x_{38}$	$x_{39}$	$x_{40}$
$x_{21}$	$x_{22}$	$x_{23}$	$x_{24}$	$x_{25}$	$x_{26}$	$x_{27}$	$x_{28}$	$x_{29}$	$x_{30}$
$x_{11}$	$x_{12}$	$x_{13}$	$x_{14}$	$x_{15}$	$x_{16}$	$x_{17}$	$x_{18}$	$x_{19}$	$x_{20}$
$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	$x_6$	$x_7$	$x_8$	$x_9$	$x_{10}$

Recall that the vector  $\mathbf{x}$  is related to the density matrix  $(f_{i,j})$  of the computational domain via

$$x_{(j-1)n+i} = f_{i,j}, \quad i, j \in \{1, \dots, n\}.$$

$$\mathbf{x} = \mathbf{f}(:) \text{ and } \mathbf{f} = \text{reshape}(\mathbf{x}, n, n)$$

## Construction of $L_H$ (periodic boundary conditions)

-1	+1	

$$\left[ \begin{array}{cc} -1 & 1 \\ & \end{array} \right]$$

## Construction of $L_H$ (periodic boundary conditions)

	-1	+1

$$\begin{bmatrix} -1 & 1 & \\ & -1 & 1 \\ & & & \end{bmatrix}$$

## Construction of $L_H$ (periodic boundary conditions)

+1		-1

$$\begin{bmatrix} -1 & 1 & \\ & -1 & 1 \\ 1 & & -1 \end{bmatrix}$$



## Construction of $L_H$ (periodic boundary conditions)

-1	+1	

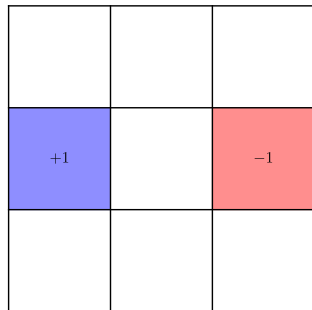
$$\begin{bmatrix} -1 & 1 & & & & & \\ & -1 & 1 & & & & \\ 1 & & -1 & & & & \\ & & & -1 & 1 & & \\ & & & & & & \end{bmatrix}$$

## Construction of $L_H$ (periodic boundary conditions)

	-1	+1

$$\begin{bmatrix} -1 & 1 & & & & & \\ & -1 & 1 & & & & \\ 1 & & -1 & & & & \\ & & & -1 & 1 & & \\ & & & & -1 & 1 & \\ & & & & & -1 & 1 \\ & & & & & & -1 & 1 \end{bmatrix}$$

## Construction of $L_H$ (periodic boundary conditions)



$$\begin{bmatrix} -1 & 1 & & & & & & & \\ & -1 & 1 & & & & & & \\ 1 & & -1 & & & & & & \\ & & & -1 & 1 & & & & \\ & & & & -1 & 1 & & & \\ & & & & & 1 & -1 & & \\ & & & & & & & 1 & -1 \end{bmatrix}$$

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-1	+1	

$$\begin{bmatrix} -1 & 1 & & & & & & & \\ & -1 & 1 & & & & & & \\ 1 & & -1 & & & & & & \\ & & & & -1 & 1 & & & \\ & & & & & -1 & 1 & & \\ & & & & & & -1 & & \\ & & & & & & & & -1 & 1 \end{bmatrix}$$



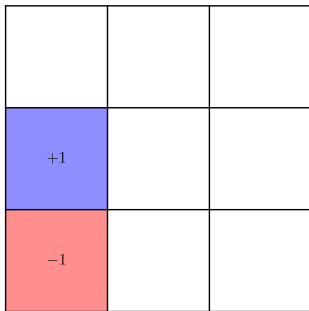


## Construction of $L_H$ (periodic boundary conditions)

$$\begin{bmatrix} -1 & 1 & & & & & & & \\ & -1 & 1 & & & & & & \\ 1 & & -1 & & & & & & \\ & & & -1 & 1 & & & & \\ & & & & -1 & 1 & & & \\ & & 1 & & & -1 & & & \\ & & & & & & -1 & 1 & \\ & & & & & & & -1 & 1 \\ & & & & & & 1 & & -1 \end{bmatrix}$$

```
n = 3;
block = spdiags([1,-1,1].*ones(n,3),[1-n,0,1],n,n);
%block = -eye(n)+diag(ones(n-1,1),1); block(end,1) = 1;
LH = [];
for ii = 1:n
    LH = blkdiag(LH,block); % form the 9x9 block matrix
end
```

# Construction of $L_V$ (periodic boundary conditions)



$-1$

$1$



## Construction of $L_V$ (periodic boundary conditions)

	+1	
	-1	

$$\begin{bmatrix} -1 & & & & & \\ & -1 & & & & \\ & & 1 & & & \\ & & & 1 & & \\ & & & & & \end{bmatrix}$$



# Construction of $L_V$ (periodic boundary conditions)

+1		
-1		

$$\begin{bmatrix} -1 & & & 1 & & & & & & & \\ & -1 & & & 1 & & & & & & \\ & & -1 & & & 1 & & & & & \\ & & & -1 & & & 1 & & & & \\ & & & & -1 & & & 1 & & & \\ & & & & & -1 & & & 1 & & \\ & & & & & & -1 & & & 1 & \\ & & & & & & & -1 & & & 1 \\ & & & & & & & & -1 & & \\ & & & & & & & & & -1 & \\ & & & & & & & & & & -1 \end{bmatrix}$$

## Construction of $L_V$ (periodic boundary conditions)

	+1	
	-1	

$$\begin{bmatrix} -1 & & & & & & & & & & \\ & -1 & & & & & & & & & \\ & & -1 & & & & & & & & \\ & & & 1 & & & & & & & \\ & & & & 1 & & & & & & \\ & & & & & -1 & & & & & \\ & & & & & & 1 & & & & \\ & & & & & & & 1 & & & \\ & & & & & & & & 1 & & \\ & & & & & & & & & 1 & \\ & & & & & & & & & & 1 \end{bmatrix}$$





# Construction of $L_V$ (periodic boundary conditions)

	-1	
	+1	

$$\begin{bmatrix} -1 & & & & & & & & & & \\ & -1 & & & & & & & & & \\ & & -1 & & & & & & & & \\ & & & 1 & & & & & & & \\ & & & & 1 & & & & & & \\ & & & & & -1 & & & & & \\ & & & & & & 1 & & & & \\ & & & & & & & 1 & & & \\ & & & & & & & & -1 & & \\ & 1 & & & & & & & & & 1 \\ & & 1 & & & & & & & & \\ & & & & & & & & & -1 & \\ & & & & & & & & & & \end{bmatrix}$$

# Construction of $L_V$ (periodic boundary conditions)

		-1
		+1

$$\begin{bmatrix} -1 & & & & 1 & & & & & & \\ & -1 & & & & 1 & & & & & \\ & & -1 & & & & 1 & & & & \\ & & & -1 & & & & 1 & & & \\ & & & & -1 & & & & 1 & & \\ & & & & & -1 & & & & 1 & \\ & 1 & & & & & & -1 & & & \\ & & 1 & & & & & & -1 & & \\ & & & 1 & & & & & & -1 & \\ & & & & & & & & & & -1 \end{bmatrix}$$





Let  $F: \mathbb{R}^N \rightarrow \mathbb{R} \cup \{+\infty\}$  and  $G: \mathbb{R}^N \rightarrow \mathbb{R} \cup \{+\infty\}$  be convex lower semicontinuous functions and  $K$  is a linear operator. Let  $F^*$  denote the *Fenchel conjugate* of  $F$ . Consider the abstract problem

$$\min_x \max_{\eta} \{\langle Kx, \eta \rangle + G(x) - F^*(\eta)\}.$$

The general form of the Chambolle–Pock algorithm can be written as

$$\eta_{k+1} = \text{prox}_{\sigma F^*}(\eta_k + \sigma K \tilde{x}_k), \quad (\text{update dual variable})$$

$$x_{k+1} = \text{prox}_{\tau G}(x_k - \tau K^T \eta_{k+1}), \quad (\text{update primal variable})$$

$$\tilde{x}_{k+1} = x_{k+1} + \theta(x_{k+1} - x_k), \quad (\text{extrapolation})$$

where  $\tau > 0$  is the primal step size,  $\sigma > 0$  is the dual step size,  $\theta > 0$  is an extrapolation parameter, and the *proximal operator* of a function  $f$  is defined as

$$\text{prox}_f(\eta) := \arg \min_x \left\{ f(x) + \frac{1}{2} \|x - \eta\|^2 \right\}.$$

If  $\sigma\tau \leq 1/L^2$ ,  $L = \|K\|_2$  (operator norm), and  $\theta = 1$ , then the algorithm can be shown to converge at linear rate  $\mathcal{O}(k^{-1})$  [Chambolle and Pock 2010].

Let us recast the TV regularization problem

$$\min_{x \geq 0} \left\{ \frac{1}{2} \|y - Ax\|^2 + \lambda \|Dx\|_1 \right\}, \quad \lambda > 0, \quad (1)$$

in the above framework.

- Note that

$$\frac{1}{2} \|Ax - y\|^2 = \max_q \left\{ \langle Ax - y, q \rangle - \frac{1}{2} \|q\|^2 \right\},$$

since  $0 = \nabla_q (\langle Ax - y, q \rangle - \frac{1}{2} \|q\|^2) = Ax - y - q$  iff  $q = Ax - y$ .

- Since  $\|x\|_1 = \sum_i |x_i| = \langle |x|, \mathbf{1} \rangle = \langle x, \text{sign}(x) \rangle$ ,

$$\lambda \|Dx\|_1 = \max_{\|z\|_\infty \leq 1} \langle Dx, \lambda z \rangle = \max_{\|z\|_\infty \leq \lambda} \langle Dx, z \rangle = \max_z \left\{ \langle Dx, z \rangle - \iota_\lambda(z) \right\},$$

where  $\iota_\lambda(z) = 0$  if  $\|z\|_\infty \leq \lambda$  and  $\iota_\lambda(z) = +\infty$  otherwise.

Then (1) is equivalent to

$$\min_x \max_{q, z} \left\{ \langle Ax - y, q \rangle + \langle Dx, z \rangle - \frac{1}{2} \|q\|^2 - \iota_\lambda(z) + \iota_+(x) \right\},$$

where  $\iota_+(x) = 0$  if  $x \geq 0$  and  $\iota_+(x) = +\infty$  otherwise.

It is easy to see that

$$\min_x \max_{q,z} \left\{ \langle Ax - y, q \rangle + \langle Dx, z \rangle - \frac{1}{2} \|q\|^2 - \iota_\lambda(z) + \iota_+(x) \right\}$$

is tantamount to

$$\min_x \max_{q,z} \left\{ \left\langle Kx, \begin{bmatrix} q \\ z \end{bmatrix} \right\rangle + G(x) - F^*(q, z) \right\},$$

where

$$G(x) = \iota_+(x),$$

$$F^*(q, z) = \langle y, q \rangle + \frac{1}{2} \|q\|^2 + \iota_\lambda(z),$$

$$K = \begin{bmatrix} A \\ D \end{bmatrix}.$$

The proximal mapping corresponding to  $G$  is simply the projection onto  $\{x \geq 0 \mid x \in \mathbb{R}^n\}$ :

$$\text{prox}_{\tau G}(x) = (\max(x_i, 0))_i = \max(x, 0).$$

On the other hand,

$$\text{prox}_{\sigma F^*}(q, z) = \left( \frac{q - \sigma y}{1 + \sigma}, \frac{\lambda z}{\max(\lambda, |z|)} \right). \quad (\text{N.B. } \eta = (q, z))$$

Noting that  $K^T = [A^T, D^T]$ , the Chambolle–Pock algorithm takes the form

$$\begin{cases} \eta_{k+1} = \text{prox}_{\sigma F^*}(\eta_k + \sigma K \tilde{x}_k) \\ x_{k+1} = \text{prox}_{\tau G}(x_k - \tau K^T \eta_{k+1}) \\ \tilde{x}_{k+1} = x_{k+1} + \theta(x_{k+1} - x_k) \end{cases}$$

$$\Leftrightarrow \begin{cases} q_{k+1} = \frac{q_k + \sigma A \tilde{x}_k - \sigma y}{1 + \sigma} \\ z_{k+1} = \frac{\lambda(z_k + \sigma D \tilde{x}_k)}{\max(\lambda, |z_k + \sigma D \tilde{x}_k|)} & (\text{elementwise division}) \\ x_{k+1} = \max(x_k - \tau A^T q_{k+1} - \tau D^T z_{k+1}, 0) & (\text{elementwise max}) \\ \tilde{x}_{k+1} = x_{k+1} + \theta(x_{k+1} - x_k). \end{cases}$$

## Pseudocode for the Chambolle–Pock algorithm

Given: projection matrix  $A$ , data  $y$ , regularization parameter  $\lambda$ .

1. Form the difference matrices  $L_H$  and  $L_V$ . Set  $D = [L_H; L_V]$ ;
2.  $L = \text{svds}([A; D], 1)$ ; % alt. use the power method
3.  $\tau = 1/L$ ,  $\sigma = 1/L$ ,  $\theta = 1$ ;
4.  $x = \text{zeros}(\text{size}(A, 2), 1)$ ,  $q = \text{zeros}(\text{size}(A, 1), 1)$ ;
5.  $z = \text{zeros}(2 * \text{size}(A, 2), 1)$ ,  $\hat{x} = x$ ;  
Repeat
  6.  $q = (q + \sigma * (A * \hat{x} - y)) / (1 + \sigma)$ ;
  7.  $z = \lambda * (z + \sigma * D * \hat{x}) ./ \max(\lambda, \text{abs}(z + \sigma * D * \hat{x}))$ ;
  8.  $x_{\text{old}} = x$ ;
  9.  $x = \max(x - \tau * A' * q - \tau * D' * z, 0)$ ;
  10.  $\hat{x} = x + \theta * (x - x_{\text{old}})$ ;until convergence.