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# Characterizing the maximum parameter of the total-variation denoising through the pseudo-inverse of the divergence

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**Abstract**—We focus on the maximum regularization parameter for anisotropic total-variation denoising. It corresponds to the minimum value of the regularization parameter above which the solution remains constant. While this value is well known for the Lasso, such a critical value has not been investigated in details for the total-variation. Though, it is of importance when tuning the regularization parameter as it allows fixing an upper-bound on the grid for which the optimal parameter is sought. We establish a closed form expression for the one-dimensional case, as well as an upper-bound for the two-dimensional case, that appears reasonably tight in practice. This problem is directly linked to the computation of the pseudo-inverse of the divergence, which can be quickly obtained by performing convolutions in the Fourier domain.

## I. INTRODUCTION

We consider the reconstruction of a  $d$ -dimensional signal (in this study  $d = 1$  or  $2$ ) from its noisy observation  $y = x + w \in \mathbb{R}^n$  with  $w \in \mathbb{R}^n$ . Anisotropic TV regularization writes, for  $\lambda > 0$ , as [1]

$$x^* = \operatorname{argmin}_{x \in \mathbb{R}^n} \frac{1}{2} \|y - x\|_2^2 + \lambda \|\nabla x\|_1 \quad (1)$$

with  $\nabla x \in \mathbb{R}^{dn}$  being the concatenation of the  $d$  components of the discrete periodical gradient vector field of  $x$ , and  $\|\nabla x\|_1 = \sum_i |(\nabla x)_i|$  being a sparsity promoting term. The operator  $\nabla$  acts as a convolution which writes in the one dimensional case ( $d = 1$ )

$$\nabla = F^+ \operatorname{diag}(K_{\rightarrow})F \quad \text{and} \quad \operatorname{div} = F^+ \operatorname{diag}(K_{\leftarrow})F \quad (2)$$

where  $\operatorname{div} = -\nabla^\top$  (where  $\top$  denotes the adjoint),  $F : \mathbb{R}^n \mapsto \mathbb{C}^n$  is the Fourier transform,  $F^+ = \operatorname{Re}[F^{-1}]$  is its pseudo-inverse and  $K_{\rightarrow} \in \mathbb{C}^n$  and  $K_{\leftarrow} \in \mathbb{C}^n$  are the Fourier transforms of the kernel functions performing forward and backward finite differences respectively. Similarly, we define in the two dimensional case ( $d = 2$ )

$$\nabla = \begin{pmatrix} F^+ & 0 \\ 0 & F^+ \end{pmatrix} \begin{pmatrix} \operatorname{diag}(K_{\downarrow}) \\ \operatorname{diag}(K_{\rightarrow}) \end{pmatrix} F \quad (3)$$

$$\text{and} \quad \operatorname{div} = F^+ \begin{pmatrix} \operatorname{diag}(K_{\uparrow}) & \operatorname{diag}(K_{\leftarrow}) \\ 0 & F \end{pmatrix} \quad (4)$$

where  $K_{\rightarrow} \in \mathbb{C}^n$  and  $K_{\leftarrow} \in \mathbb{C}^n$  (resp.  $K_{\downarrow} \in \mathbb{C}^n$  and  $K_{\uparrow} \in \mathbb{C}^n$ ) perform forward and backward finite difference in the horizontal (resp. vertical) direction.

## II. GENERAL CASE

For the general case, the following proposition provides an expression of the maximum regularization parameter  $\lambda_{\max}$  as the solution of a convex but non-trivial optimization problem (direct consequence of the Karush-Khun-Tucker condition).

**Proposition 1.** Define for  $y \in \mathbb{R}^n$ ,

$$\lambda_{\max} = \min_{\zeta \in \operatorname{Ker}[\operatorname{div}]} \|\operatorname{div}^+ y + \zeta\|_{\infty} \quad (5)$$

where  $\operatorname{div}^+$  is the Moore-Penrose pseudo-inverse of  $\operatorname{div}$  and  $\operatorname{Ker}[\operatorname{div}]$  its null space. Then,  $x^* = \frac{1}{n} \mathbb{1}_n \mathbb{1}_n^\top y$  if and only if  $\lambda \geq \lambda_{\max}$ .

## III. ONE DIMENSIONAL CASE

In the 1d case,  $\operatorname{Ker}[\operatorname{div}] = \operatorname{Span}[\mathbb{1}_n]$  and thus the optimization problem can be solved by computing  $\operatorname{div}^+$  in the Fourier domain, in  $O(n \log n)$  operations, as shown in the next corollary.

**Corollary 1.** For  $d = 1$ ,  $\lambda_{\max} = \frac{1}{2} [\max(\operatorname{div}^+ y) - \min(\operatorname{div}^+ y)]$ ,

$$\text{where} \quad \operatorname{div}^+ = F^+ \operatorname{diag}(K_{\uparrow}^+)F \quad (6)$$

$$\text{and} \quad (K_{\uparrow}^+)_i = \begin{cases} \frac{(K_{\uparrow})_i^*}{|(K_{\uparrow})_i|^2} & \text{if } |(K_{\uparrow})_i|^2 > 0 \\ 0 & \text{otherwise} \end{cases},$$

and  $*$  denotes the complex conjugate.

Note that the condition  $|(K_{\uparrow})_i|^2 > 0$  is satisfied everywhere except for the zero frequency. In the non-periodical case,  $\operatorname{div}$  is the incidence matrix of a tree whose pseudo-inverse can be obtained following [2].

## IV. TWO DIMENSIONAL CASE

In the 2d case,  $\operatorname{Ker}[\operatorname{div}]$  is the orthogonal of the vector space of signals satisfying Kirchhoff's voltage law on all cycles of the periodical grid. Its dimension is  $n+1$ . It follows that the optimization problem becomes much harder. Since our motivation is only to provide an approximation of  $\lambda_{\max}$ , we propose to compute an upper-bound in  $O(n \log n)$  operations thanks to the following corollary.

**Corollary 2.** For  $d = 2$ ,  $\lambda_{\max} \leq \underbrace{\frac{1}{2} [\max(\operatorname{div}^+ y) - \min(\operatorname{div}^+ y)]}_{\lambda_{\text{bnd}}}$ ,

$$\text{where} \quad \operatorname{div}^+ = \begin{pmatrix} F^+ & 0 \\ 0 & F^+ \end{pmatrix} \begin{pmatrix} \operatorname{diag}(\tilde{K}_{\uparrow}^+) \\ \operatorname{diag}(\tilde{K}_{\leftarrow}^+) \end{pmatrix} F, \quad \text{and} \quad (7)$$

$$(\tilde{K}_{\uparrow}^+)_i = \begin{cases} \frac{(K_{\uparrow})_i^*}{|(K_{\uparrow})_i|^2 + |(K_{\leftarrow})_i|^2} & \text{if } |(K_{\uparrow})_i|^2 + |(K_{\leftarrow})_i|^2 > 0 \\ 0 & \text{otherwise} \end{cases},$$

$$(\tilde{K}_{\leftarrow}^+)_i = \begin{cases} \frac{(K_{\leftarrow})_i^*}{|(K_{\uparrow})_i|^2 + |(K_{\leftarrow})_i|^2} & \text{if } |(K_{\uparrow})_i|^2 + |(K_{\leftarrow})_i|^2 > 0 \\ 0 & \text{otherwise} \end{cases}.$$

Note that the condition  $|(K_{\uparrow})_i|^2 + |(K_{\leftarrow})_i|^2 > 0$  is again satisfied everywhere except for the zero frequency. Remark also that this result can be straightforwardly extended to the case where  $d > 2$ .

## V. RESULTS AND DISCUSSION

Figure 1 and 2 provide illustrations of the computation of  $\lambda_{\max}$  and  $\lambda_{\text{bnd}}$  on a 1d signal and a 2d image respectively. The convolution kernel is a simple triangle wave in the 1d case but is more complex in the 2d case. The operator  $\operatorname{div} \operatorname{div}^+$  is in fact the projector onto the space of zero-mean signals, i.e.,  $\operatorname{Im}[\operatorname{div}]$ . Figure 3 illustrates the evolution of  $x^*$  with respect to  $\lambda$  (computed with the algorithm of [3]). Our upper-bound  $\lambda_{\text{bnd}}$  (computed in  $\sim 5$ ms) appears to be reasonably tight ( $\lambda_{\max}$  computed in  $\sim 25$ s with [3] on Problem (5)).

Future work will concern the generalization of these results to other  $\ell_1$  analysis regularization and to ill-posed inverse problems.

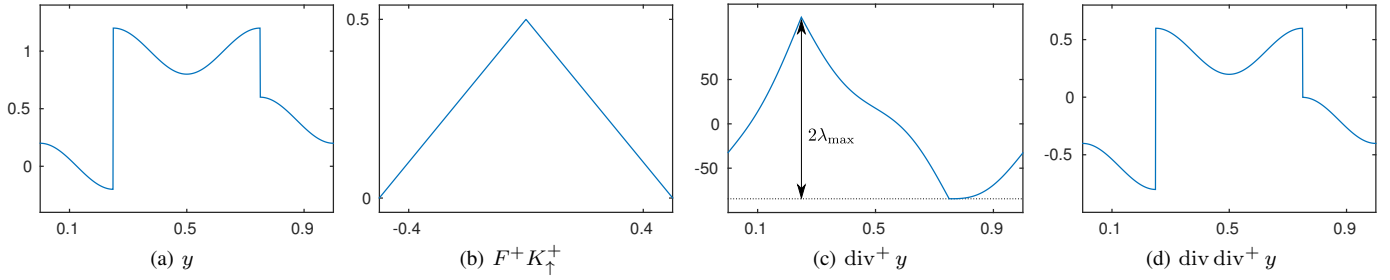


Fig. 1. (a) A 1d signal  $y$ . (b) The convolution kernel  $F^+K_{\uparrow}^+$  that realizes the pseudo inversion of the divergence. (c) The signal  $\text{div}^+ y$  on which we can read the value of  $\lambda_{\max}$ . (d) The signal  $\text{div div}^+ y$  showing that one can reconstruct  $y$  from  $\text{div}^+ y$  up to its mean component.

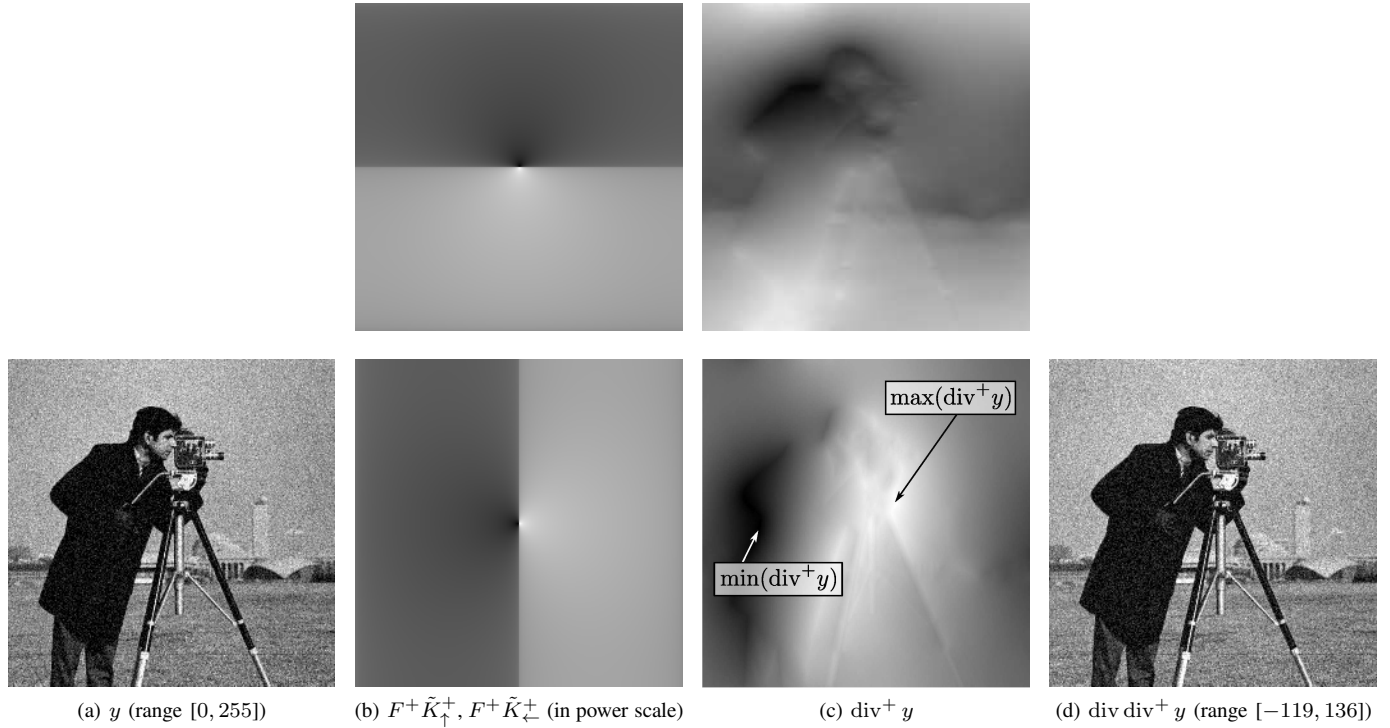


Fig. 2. (a) A 2d signal  $y$ . (b) The convolution kernels  $F^+K_{\uparrow}^+$  and  $F^+K_{\downarrow}^+$  that realizes the pseudo inversion of the divergence. (c) The absolute value of the two coordinates of the vector field  $\text{div}^+ y$  on which we can read the upper-bound  $\lambda_{\text{bnd}}$  of  $\lambda_{\max}$ . (d) The image  $\text{div div}^+ y$  showing again that one can reconstruct  $y$  from  $\text{div}^+ y$  up to its mean component.

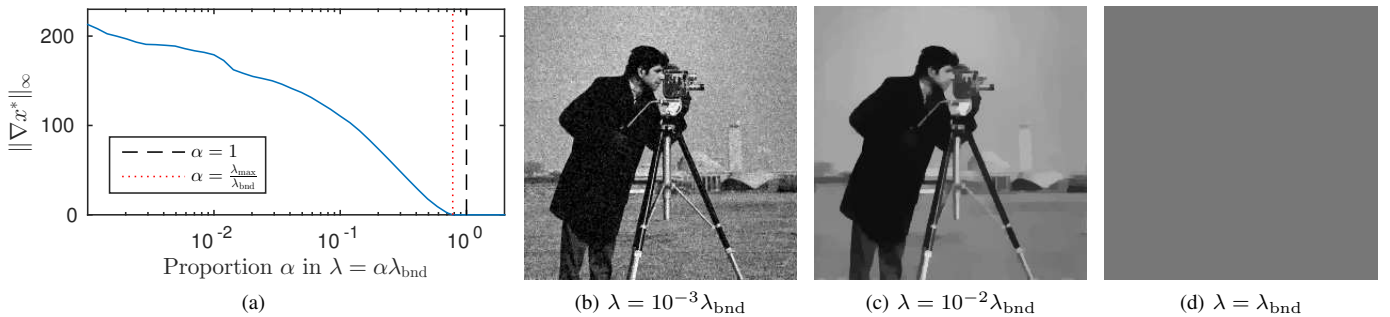


Fig. 3. (a) Evolution of  $\|\nabla x^*\|_{\infty}$  as a function of  $\lambda$ . (b), (c), (d) Results  $x^*$  of the periodical anisotropic total-variation for three different values of  $\lambda$ .

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