

# Assignment 3

## Convex Optimization SS2022

Martin Zach (martin.zach@icg.tugraz.at)

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**Submission:** Upload your report as a single pdf-file ( $\leq 10\text{MB}$ ) to the TeachCenter and include your implementation (`main.py`) in your submission.

**Deadline:** June, 6<sup>th</sup> 2022, 18:00

### The ROF model for image denoising (10P)

In this task, we would like to reconstruct images degraded by additive Gaussian noise, see Figure 1. We use the well-studied Rudin, Osher and Fatemi (ROF) model [1], also known as TV- $\ell^2$  model, which yields good results despite its simplicity. Let  $\mathbf{u}_0 \in \mathbb{R}^{3n}$  be the observed noisy image of size  $n = n_1 \times n_2$  with 3 color channels, the discrete version of the ROF model using a finite difference discretization of images is defined as

$$\min_{\mathbf{u} \in \mathbb{R}^n} \left\{ E_P(\mathbf{u}) := \lambda \|D\mathbf{u}\|_{2,1} + \frac{1}{2} \|\mathbf{u} - \mathbf{u}_0\|_2^2 \right\}, \quad (\text{P})$$

where  $\mathbf{u} \in \mathbb{R}^{3n}$  is the denoised image and  $\lambda$  is a parameter balancing the tradeoff between regularization and data fidelity. The regularization term is given by the isotropic total variation for color images that utilizes the finite difference operator  $D \in \mathbb{R}^{6n \times 3n}$  defined as

$$D = \begin{pmatrix} D_x & 0 & 0 \\ D_y & 0 & 0 \\ 0 & D_x & 0 \\ 0 & D_y & 0 \\ 0 & 0 & D_x \\ 0 & 0 & D_y \end{pmatrix}$$

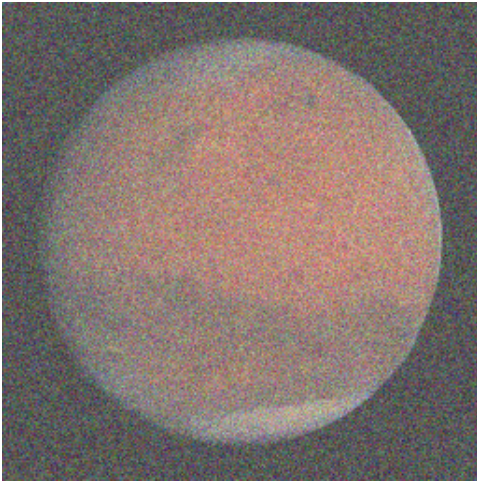


Figure 1: Left noisy observed image  $\mathbf{u}_0$  and right the original uncorrupted image of Mars.

using the operators  $D_x, D_y \in \mathbb{R}^{n \times n}$

$$D_x = \begin{pmatrix} -1 & 1 & 0 & \cdots \\ 0 & -1 & 1 & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{pmatrix} \quad D_y = \begin{pmatrix} -1 & 0 & \cdots & 0 & 1 & 0 & \cdots \\ 0 & -1 & \cdots & 0 & 0 & 1 & \cdots \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots \end{pmatrix},$$

which extract image gradients in  $x/y$  direction assuming a lexicographic ordering of the image pixels and Neumann boundary conditions. Let  $\mathbf{z} \in \mathbb{R}^{6n}$ , we define the  $\ell^{2,1}$ -norm as follows:

$$\|\mathbf{z}\|_{2,1} = \sum_{i=1}^n \sqrt{\sum_{j=0}^5 (z_{i+jn})^2}.$$

Here, we would like to solve this method by means of dualization and the application of the proximal gradient method as well as FISTA. Your tasks are as follows:

- Show that the dual problem of (P) is given by

$$\max_{\mathbf{p} \in \mathbb{R}^{6n}} \left\{ E_D(\mathbf{p}) := -\frac{1}{2} \|D^\top \mathbf{p}\|_2^2 + \langle D^\top \mathbf{p}, \mathbf{u}_0 \rangle - \delta_{B_{\|\cdot\|_{2,\infty}}[0,\lambda]}(\mathbf{p}) \right\}, \quad (\text{D})$$

where  $\mathbf{p} \in \mathbb{R}^{6n}$  is the dual variable and

$$B_{\|\cdot\|_{2,\infty}}[0,\lambda] = \left\{ \mathbf{p} \in \mathbb{R}^{6n} : \sqrt{\sum_{j=0}^5 (p_{i+jn})^2} \leq \lambda \text{ for } i = 1, \dots, n \right\}.$$

Explain each step in your derivation.

- Show that the primal solution  $\mathbf{u}$  can be obtained from the dual  $\mathbf{p}$  by

$$\mathbf{u} = \mathbf{u}_0 - D^\top \mathbf{p}. \quad (1)$$

- Prove that

$$\|D\|_2 \leq \sqrt{8}.$$

- Implement proximal gradient ascent as well as FISTA to solve the dual ROF problem (D).

Compare both algorithms for  $\lambda \in \{0.25, 1.0, 4.0\}$ :

- Include a logarithmic plot of the dual energy (D) and the primal energy (P) for both algorithms in your report.  
*Hint:* Use (1) to convert dual variables to corresponding primal variables.
- Discuss the convergence rates of both algorithms and recommend the faster one.
- What is the influence of  $\lambda$  on the convergence?
- Include the resulting image  $\mathbf{u}$  and the dual variable  $\mathbf{p}$  in your report and discuss their structure.
- Plot the primal-dual gap  $G(\mathbf{u}, \mathbf{p}) = E_P(\mathbf{u}) - E_D(\mathbf{p})$  over the iterations for both algorithms.

## Fenchel conjugate (5P)

- Compute the Fenchel conjugate of  $f : \mathbb{R} \rightarrow \mathbb{R}$ , where  $f$  is given by

1.  $f(\mathbf{x}) = \frac{|\mathbf{x}|^p}{p}$  for  $p \in (1, \infty)$ ,
2.  $f(\mathbf{x}) = \exp(\mathbf{x})$ ,
3.  $f(\mathbf{x}) = \cosh(\mathbf{x})$ ,
4.  $f(\mathbf{x}) = \sqrt{1 + \mathbf{x}^2}$ .

- Let  $f, g : \mathbb{E} \rightarrow (-\infty, \infty]$  and  $\alpha \in (0, 1)$ . Show that

$$(\alpha f + (1 - \alpha)g)^* \leq \alpha f^* + (1 - \alpha)g^*.$$

## Infimal convolution (6P)

- Let  $f : \mathbb{E} \rightarrow (-\infty, \infty]$  be proper, lower semicontinuous and convex. Set  $g_0 = \delta_{\{0\}}$  and  $g_{n+1} = f \square g_n$  for  $n \in \mathbb{N}$ . Prove that

$$g_n(\mathbf{x}) = n f\left(\frac{\mathbf{x}}{n}\right)$$

for all  $n \geq 1$ .

- Let  $f : \mathbb{E} \rightarrow (-\infty, \infty]$  be subadditive such that  $f(\mathbf{0}) = 0$ . Show that  $f \square f = f$ . Recall that a function  $f : \mathbb{E} \rightarrow (-\infty, \infty]$  is subadditive if  $f(\mathbf{x} + \mathbf{y}) \leq f(\mathbf{x}) + f(\mathbf{y})$  for all  $\mathbf{x}, \mathbf{y} \in \text{dom}(f)$ .

## Proximal map (4P)

Compute the proximal map for  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  given by

1.  $f(\mathbf{x}) = \frac{1}{2} \mathbf{x}^\top A \mathbf{x} + \mathbf{b}^\top \mathbf{x} + c$ , where  $A \in \mathbb{R}^{n \times n}$  is positive definite,  $\mathbf{b} \in \mathbb{R}^n$  and  $c \in \mathbb{R}$ ,
2.  $f(\mathbf{x}) = \|\mathbf{x}\|_2$ ,
3.  $f(\mathbf{x}) = \|\mathbf{x}\|_1$ ,
4.  $f(\mathbf{x}) = -\sum_{i=1}^n \log x_i$ .

## References

- [1] L. Rudin, S. Osher, and E. Fatemi. Nonlinear total variation based noise removal algorithms. *Physica D*, 60:259–268, 1992.