An image is a function $\Omega$ to $\mathbb{R}$.

A matrix is a discrete function.

Let $u$ be an image, $f$ the observed image.

The data fidelity/discrepancy function is (page ...)

$$F(u) = \frac{1}{2}||u - f||_2^2 \tag{1}$$

The regularisation term is (page 14)

$$\mathrm{TGV}_\alpha^2(u) = \max \left\{ \langle u, \mathrm{div}_h v \rangle_U \;\middle|\; \begin{array}{l} (v, w) \in V \times W,\ \mathrm{div}_h w = v, \\ \|w\|_\infty \leq \alpha_0,\ \|v\|_\infty \leq \alpha_1 \end{array} \right\} \tag{2}$$

where $\langle u, \mathrm{div}_h v \rangle_U$ is ...

The total generalized variation (TGV) functional is defined as (page ...)

$$\min_{u \in L^p(\Omega)} F(u) + \mathrm{TGV}_\alpha^2(u) \tag{3}$$

The $x$ and $y$ forward finite difference operators are (page 13)

$$(\partial_x^+ u)_{i,j} = \begin{cases} u_{i+1,j} - u_{i,j} & \text{for } 1 \leq i < N_1, \\ 0 & \text{for } i = N_1, \end{cases} \tag{4}$$

$$(\partial_y^+ u)_{i,j} = \begin{cases} u_{i,j+1} - u_{i,j} & \text{for } 1 \leq j < N_2, \\ 0 & \text{for } j = N_2, \end{cases} \tag{5}$$

and the backward finite difference operators are (page 13)

$$(\partial_x^- u)_{i,j} = \begin{cases} u_{1,j} & \text{if } i = 1, \\ u_{i,j} - u_{i-1,j} & \text{for } 1 < i < N_1, \\ -u_{N_1-1,j} & \text{for } i = N_1, \end{cases} \tag{6}$$

$$(\partial_y^- u)_{i,j} = \begin{cases} u_{i,1} & \text{if } j = 1, \\ u_{i,j} - u_{i,j-1} & \text{for } 1 < j < N_2, \\ -u_{i,N_2-1} & \text{for } j = N_2, \end{cases} \tag{7}$$