

# Visualization and Imaging

## Exercise Sheet 1

### Exercise 1:

Implement the marching squares algorithm in MATLAB such that it takes a 2-D image  $f$  (i.e., a matrix  $I_f \in \mathbb{R}_+^{N \times M}$ ) and a threshold  $K$  as input and eventually plots the resulting isocurve corresponding to the threshold  $K$ .

### Exercise 2:

Regard the functional

$$\mathcal{F}(u) = \int_{\mathbb{S}^2} \left( \nabla_{\mathbb{S}^2} f(t, x) \cdot u(x) + \frac{\partial}{\partial t} f(t, x) \right)^2 dS(x) + \|u\|_{H_1(\mathbb{S}^2)}^2,$$

which we have derived for optical flow on the sphere  $\mathbb{S}^2 = \{x \in \mathbb{R}^3 : |x| = 1\}$ . Let  $\{y_n\}_{n \in \mathbb{N}}$  be a dense orthonormal function system in  $L^2(\mathbb{S}^2, \mathbb{R}^3)$ , i.e.,

$$\int_{\mathbb{S}^2} y_n(x) \cdot y_m(x) dS(x) = \begin{cases} 0, & n \neq m, \\ 1, & n = m, \end{cases}$$

and

$$u(x) = \sum_{n=0}^{\infty} \alpha_n y_n(x), \tag{1}$$

for adequate coefficients  $\alpha_n \in \mathbb{R}$ . Furthermore, we may assume that the squared norm  $\|u\|_{H_1(\mathbb{S}^2)}^2$  can be expressed as

$$\|u\|_{H_1(\mathbb{S}^2)}^2 = \sum_{n=0}^{\infty} \alpha_n^2 w_n,$$

for some known weights  $w_n \in \mathbb{R}_+$ . At last, let us assume that  $u$  from (1) can be expressed by a finite sum

$$u(x) = \sum_{n=0}^N \alpha_n y_n(x), \tag{2}$$

for some predefined maximum  $N \in \mathbb{N}$ . In other words, the function  $u$  is defined by the coefficients  $\alpha_n$ ,  $n = 0, \dots, N$ .

Under the conditions above, show that the minimizer  $u$  of the functional  $\mathcal{F}$  can be determined by solving the linear equation

$$(A + D)\alpha = b,$$

where  $\alpha = (\alpha_0, \dots, \alpha_N)^T$  and

$$\begin{aligned}
 A &= (A_{n,m})_{n,m=0,\dots,N}, & A_{n,m} &= \int_{\mathbb{S}^2} (\nabla_{\mathbb{S}^2} f(t, x) \cdot y_n(x)) (\nabla_{\mathbb{S}^2} f(t, x) \cdot y_m(x)) dS(x), \\
 D &= (D_{n,m})_{n,m=0,\dots,N}, & D_{n,m} &= \begin{cases} 0, & n \neq m, \\ w_n, & n = m, \end{cases} \\
 b &= (b_0, \dots, b_N)^T, & b_n &= - \int_{\mathbb{S}^2} (\nabla_{\mathbb{S}^2} f(t, x) \cdot y_n(x)) \frac{\partial}{\partial t} f(t, x) dS(x)
 \end{aligned}$$

**Exercise 3:**

Regard the functional

$$\mathcal{F}(g) = \alpha \int_{\Omega} |\nabla g(x)|^2 dx + \mu \int_{\Omega} (g(x) - f(x))^2 dx$$

for some possibly noisy image  $f \in L^2(\Omega, \mathbb{R})$  and a (smoothed) filtered version  $g \in L^2(\Omega, \mathbb{R})$  (additionally assuming that  $\nabla g \in L^2(\Omega, \mathbb{R}^3)$ ), where  $\Omega = [0, 1]^2 \subset \mathbb{R}^2$ . Show that minimizing the functional  $\mathcal{F}$  is equivalent to solving the differential equation

$$\begin{aligned}
 -\alpha \Delta g(x) + \mu g(x) &= \mu f(x), & x \in \Omega \\
 \frac{\partial}{\partial \nu} g(x) &= 0, & x \in \partial\Omega,
 \end{aligned}$$

where  $\frac{\partial}{\partial \nu} g$  denotes the normal derivative of  $g$  on the boundary  $\partial\Omega$  of  $\Omega$ . (Hint: Compute the first variation and use Green's identities)

**Remark:** Using a steepest descent method, one could also derive the reaction diffusion equation

$$\begin{aligned}
 \frac{\partial}{\partial t} g(t, x) &= \alpha \Delta g(t, x) + \mu (f(x) - g(t, x)), & x \in \Omega, t > 0, \\
 \frac{\partial}{\partial \nu} g(t, x) &= 0, & x \in \partial\Omega, t > 0,
 \end{aligned}$$

for adequate initial conditions  $g(0, x)$ . Compare this to diffusion filtering described in the lecture.