Image Denoising

Homework n°7 - Exercises

Exercise 2.1

$$E_{\theta}^{\text{FoE}}(u,v) = \frac{1}{2\sigma^2} \|u - v\|^2 + \sum_{x \in \Omega} \sum_{i=1}^{N} \phi_i(\mathbf{k}_i * u(x)) + \text{constants}$$

For $x \in \Omega$, we have, if \mathbf{k}_i is of size $n \times n$: $\mathbf{k}_i * u(x) = \sum_{j_1, j_2 = -n}^{n} \mathbf{k}_i (x_1 - j_1, x_2 - j_2) u(j_1, j_2)$.

So

$$\frac{\partial (\mathbf{k}_i * u(x))}{\partial u_{j_1, j_2}} = \mathbf{k}_i (x_1 - j_1, x_2 - j_2).$$

Then, we have

$$\frac{\partial \phi_i \left(\mathbf{k}_i * u(x)\right)}{\partial u_{j_1,j_2}} = \mathbf{k}_i (x_1 - j_1, x_2 - j_2) \phi_i' \left(\mathbf{k}_i * u(x)\right),$$

and

$$\frac{\partial}{\partial u_{j_1,j_2}} \left(\sum_{x \in \Omega} \sum_{i=1}^{N} \phi_i(\mathbf{k}_i * u(x)) \right) = \sum_{x \in \Omega} \sum_{i=1}^{N} \mathbf{k}_i (x_1 - j_1, x_2 - j_2) \phi_i' (\mathbf{k}_i * u(x))$$

$$= \sum_{i=1}^{N} \left(\overline{\mathbf{k}_i} * \phi_i' (\mathbf{k}_i * u) \right)_{j_1,j_2},$$

where we used

$$\left(\overline{\mathbf{k}_i} * \phi_i'(\mathbf{k}_i * u)\right)_{j_1, j_2} = \sum_{x \in \Omega} \mathbf{k}_i(x_1 - j_1, x_2 - j_2) \phi_i'(\mathbf{k}_i * u(x)).$$

Therefore, we have

$$\nabla E_{\theta}^{\text{FoE}}(u, v) = \frac{1}{\sigma^2}(u - v) + \sum_{i=1}^{N} \overline{\mathbf{k}_i} * \phi_i' (\mathbf{k}_i * u).$$

Therefore the gradient descent reads
$$u^{t+1} = u^t - \eta \left(\frac{1}{\sigma^2} (u^t - v) + \sum_{i=1}^N \overline{\mathbf{k}_i} * \phi_i' \left(\mathbf{k}_i * u^t \right) \right)$$

Exercise 2.2

$$\mathcal{L}_{\infty}(\theta) = \int \log p_{\theta}(u) p(u) du$$

$$= -\int \log \left(\frac{p(u)}{p_{\theta}(u)}\right) p(u) du + \int \log p(u) p(u) du$$

$$= -\text{KL}\left(p(u) \mid\mid p_{\theta}(u)\right) + \text{constant.}$$

Therefore maximizing $\mathcal{L}_{\infty}(\theta)$ is equivalent to minimizing KL $(p(u) || p_{\theta}(u))$.