

Example on image sharpening:

Given an image $(\bar{I}(x,y))_{-N \leq x,y \leq N}$ with DFT $(\hat{\bar{I}}(u,v))_{-N \leq u,v \leq N}$.

Suppose we perform unsharp masking $(H(u,v))_{-N \leq u,v \leq N}$

using Gaussian filter with standard deviation σ to $\hat{\bar{I}}$.

If $H(2,2) = \frac{26}{25}$, Find σ^2 .

Sol:

Recall: Image sharpening = Add back high frequency components.

Given f , we aim to find $g = f + k(f - f_{\text{smooth}})$

$$\text{DFT}(g)(u,v) = \left(\underset{1+kH_{\text{HP}}(u,v)}{1+k(1-H_{\text{LP}}(u,v))} \right) \text{DFT}(f)(u,v)$$

when $k=1$, it is called unsharp masking.

For this question,

first we write down the formula of low-pass Gaussian filter:

$$H_{\text{LP}}(u,v) = \exp\left(-\frac{u^2+v^2}{2\sigma^2}\right) \quad \exp\left(-\frac{u^2+v^2}{2\sigma^2}\right) \quad 1 - \exp\left(-\frac{u^2+v^2}{2\sigma^2}\right)$$

$$\text{So, } 1 + 1 - \exp\left(-\frac{4+4}{2\sigma^2}\right) = \frac{26}{25}$$

$$\Rightarrow \exp\left(-\frac{8}{2\sigma^2}\right) = \frac{24}{25}$$

$$\Rightarrow \sigma^2 = \frac{4}{\log \frac{25}{24}}$$

$$\begin{array}{l} (0,0) \quad \exp\left(-\frac{0}{2\sigma^2}\right) = 1 \\ 1 - \exp\left(-\frac{0}{2\sigma^2}\right) = 0 \end{array}$$

Image denoising in the spatial domain

Example: Chapter 4 Ex 4.

4. Derive the anisotropic diffusion equation:

$$\frac{\partial I(x, y; \sigma)}{\partial \sigma} = \nabla \cdot (K(x, y) \nabla I(x, y; \sigma))$$

from minimizing the following energy functional:

$$E(I) = \int_{\Omega} \underbrace{K(x, y)}_{\text{given}} \|\nabla I(x, y)\|^2 dx dy.$$

We assume the continuous setting.

An grayscale image $I: \underbrace{[0, M] \times [0, N]}_{\text{spatial domain}} \rightarrow \underbrace{[0, 1]}_{\text{color intensity}}$ denotes a function under certain conditions.

We then derive the PDE from the energy using calculus of variations.

Suppose f is the minimizer of the energy $E(I)$.

Then, for any function $g: [0, M] \times [0, N] \rightarrow [0, 1]$,

we have $E(f+tg) \geq E(f)$.

So, $\left. \frac{d}{dt} E(f+tg) \right|_{t=0} \geq 0$ for any g .

$$\begin{aligned} E(f+tg) &= \int_{\Omega} K(x, y) \|\nabla(f+tg)(x, y)\|^2 dx dy \\ &= \int_{\Omega} K(x, y) \|\nabla f(x, y) + t \nabla g(x, y)\|^2 dx dy \\ &= \int_{\Omega} K(x, y) \langle \nabla f(x, y) + t \nabla g(x, y), \nabla f(x, y) + t \nabla g(x, y) \rangle dx dy \\ &= \int_{\Omega} K(x, y) \left(\|\nabla f(x, y)\|^2 + 2t \langle \nabla f(x, y), \nabla g(x, y) \rangle + \underbrace{\|\nabla g(x, y)\|^2}_{t^2} \right) dx dy \end{aligned}$$

So, $\left. \frac{d}{dt} E(f+tg) \right|_{t=0}$

$$\begin{aligned}
&= \frac{d}{dt} \int_{\Omega} K(x,y) \left(\|\nabla f(x,y)\|^2 + 2t \underbrace{\langle \nabla f(x,y), \nabla g(x,y) \rangle}_{\hat{t}^2} + \|\nabla g(x,y)\|^2 \right) dx dy \Big|_{t=0} \\
&= \int_{\Omega} \frac{d}{dt} \left(K(x,y) \left(\|\nabla f(x,y)\|^2 + \underbrace{2t \langle \nabla f(x,y), \nabla g(x,y) \rangle}_{\hat{t}^2} + \|\nabla g(x,y)\|^2 \right) \right) \Big|_{t=0} dx dy \\
&= \int_{\Omega} 2 K(x,y) \nabla f(x,y) \cdot \nabla g(x,y) dx dy \geq 0 \quad (*) \quad \frac{dt^2}{dt} = 2t
\end{aligned}$$

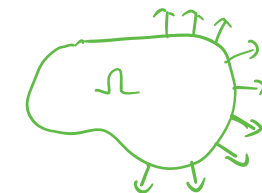
If $(*) = \int_{\Omega} g V(f)$ for some functional $V(f)$,

then $\int_{\Omega} g V(f) \geq 0$ for any g

$$\Rightarrow V(f) = 0$$

We apply divergence theorem to achieve it. $\int_{\Omega} \nabla \cdot \vec{F} = \int_{\partial\Omega} \vec{F} \cdot \vec{n}$

$$\begin{aligned}
&\int_{\Omega} \nabla \cdot (g(x,y) K(x,y) \nabla f(x,y)) dx dy = \int_{\partial\Omega} g(x,y) K(x,y) \nabla f(x,y) \cdot \underbrace{\vec{n}(x,y)}_{\text{outward pointing normal at } (x,y)} d\sigma \\
&= \int_{\Omega} \nabla g(x,y) \cdot (K(x,y) \nabla f(x,y)) dx dy \\
&+ \int_{\Omega} g(x,y) \nabla \cdot (K \nabla f)(x,y) dx dy
\end{aligned}$$



$$\text{So, } \frac{1}{2} (*) = \int_{\partial\Omega} g(x,y) K(x,y) \nabla f(x,y) \cdot \vec{n}(x,y) d\sigma$$

$$- \int_{\Omega} g(x,y) \nabla \cdot (K \nabla f)(x,y) dx dy \geq 0 \text{ for any } g.$$

$$\text{So, } \begin{cases} K(x,y) \nabla f(x,y) \cdot \vec{n}(x,y) = 0 & \text{on } \partial\Omega \\ \nabla \cdot (K \nabla f)(x,y) = 0 & \text{on } \Omega. \end{cases}$$

$$\Rightarrow \frac{\partial I(x,y; \delta)}{\partial \delta} = \nabla \cdot (K(x,y) \nabla I(x,y; \delta))$$

In the discrete case, how to solve this equation?

Starting from an initial image $f^{(0)}$,

we perform gradient descent to obtain the denoised image.

Observation:

Suppose f is not a minimizer,

we want to find some g , s.t.,

$\bar{E}(f+tg) < \bar{E}(f)$ for small $t > 0$.

Note that $\frac{d}{dt} \Big|_{t=0} \frac{1}{2} \bar{E}(f+tg)$

$$= \int_{\partial\Omega} g(x,y) K(x,y) \nabla f(x,y) \cdot \vec{n}(x,y) d\sigma \quad \text{ignore this term,}$$

$$- \int_{\Omega} g(x,y) \nabla \cdot (K \nabla f)(x,y) dx dy$$

If we choose $g(x,y) = \nabla \cdot (K \nabla f)$, $-\int_{\Omega} (\nabla \cdot (K \nabla f))^2 dx dy \leq 0$

then $\frac{d}{dt} \Big|_{t=0} \frac{1}{2} \bar{E}(f+tg) < 0$

$\Rightarrow \bar{E}(f+tg) < \bar{E}(f)$.

So, in each iteration, we need to discretize the descent direction

$\nabla \cdot (K \nabla f^{(k)})$, then let $f^{(k+1)}(x,y) = f^{(k)}(x,y) + t \nabla \cdot (K \nabla f^{(k)})(x,y)$.

We apply a finite difference scheme.

Given $f^{(k)}(u,v)$, $0 \leq u, v \leq N$.

Recall given vector field $\vec{F} = \begin{pmatrix} f_1 \\ f_2 \end{pmatrix}$,

$$\nabla \cdot \vec{F} = \frac{\partial f_1}{\partial x} + \frac{\partial f_2}{\partial y}$$

$$\text{So, } \nabla \cdot (K \nabla f^{(k)}) (u, v)$$

$$= \nabla \cdot \left(K \begin{pmatrix} \frac{\partial f^{(k)}}{\partial x} \\ \frac{\partial f^{(k)}}{\partial y} \end{pmatrix} \right) (u, v) = \frac{\partial}{\partial x} \left(K \frac{\partial f^{(k)}}{\partial x} \right) (u, v) + \frac{\partial}{\partial y} \left(K \frac{\partial f^{(k)}}{\partial y} \right) (u, v)$$

$$\left(\text{Here we use } \frac{\partial g}{\partial x} (u, v) \approx g(u+1, v) - g(u, v), \frac{\partial g}{\partial y} (u, v) \approx g(u, v+1) - g(u, v) \right)$$

$$\approx \left(K \frac{\partial f^{(k)}}{\partial x} \right) (u+1, v) - \left(K \frac{\partial f^{(k)}}{\partial x} \right) (u, v)$$

$$+ \left(K \frac{\partial f^{(k)}}{\partial y} \right) (u, v+1) - \left(K \frac{\partial f^{(k)}}{\partial y} \right) (u, v)$$

$$\left(\text{Here we use } \frac{\partial g}{\partial x} (u, v) \approx g(u, v) - g(u-1, v), \frac{\partial g}{\partial y} (u, v) \approx g(u, v) - g(u, v-1) \right)$$

$$\approx K(u+1, v) (f(u+1, v) - f(u, v)) - K(u, v) (f(u, v) - f(u-1, v))$$

$$+ K(u, v+1) (f(u, v+1) - f(u, v)) - K(u, v) (f(u, v) - f(u, v-1))$$

(Remark: you can use other methods to discretize

$$\nabla f, \nabla \cdot (\nabla f), \dots,$$

$$\text{s.t., } \frac{\partial f}{\partial x} (u, v) \approx f(u+1, v) + f(u-1, v) - 2f(u, v)$$

For more details and theories, take MATH 3240)

