

# 1 Written Part

## 1(a) $K^2HW$

If the filter is not separable, then the process of performing a convolution requires  $K \cdot K$  operations per pixel, and since the image has  $H \cdot W$  pixels in total, so the number of operations would be  $K^2HW$ .

## 1(b) $2KHW$

If the filter is separable, this operation could be speed up by first performing a 1D horizontal convolution followed by a 1D vertical convolution, then the process of performing a convolution requires  $K + K$  operations per pixel, and since the image has  $H \cdot W$  pixels in total, so the number of operations would be  $2KHW$ .

**2(a)** A vertical derivative,  $\frac{\partial G(x,y)}{\partial y}$ , of a Gaussian filter  $G$  is a separable filter for both isotropic and anisotropic cases.

### 2(a).01 isotropic Gaussian filter

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

$$\frac{\partial G(x,y)}{\partial y} = -\frac{y}{2\pi\sigma^4} e^{-\frac{x^2+y^2}{2\sigma^2}} = \left[-\frac{1}{\sigma^2\sqrt{2\pi}} e^{-\frac{x^2}{2\sigma^2}}\right] \cdot \left[\frac{y}{\sigma^2\sqrt{2\pi}} e^{-\frac{y^2}{2\sigma^2}}\right]$$

Since the above function could be converted into  $f(x) \cdot f(y)$ , so it's a separable filter.

### 2(a).02 anisotropic Gaussian filter

$$G(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} e^{-\left(\frac{x^2}{2\sigma_x^2} + \frac{y^2}{2\sigma_y^2}\right)}$$

$$\frac{\partial G(x,y)}{\partial y} = -\frac{y}{2\pi\sigma_x\sigma_y^3} e^{-\left(\frac{x^2}{2\sigma_x^2} + \frac{y^2}{2\sigma_y^2}\right)} = \left[-\frac{1}{\sigma_x\sqrt{2\pi}} e^{-\frac{x^2}{2\sigma_x^2}}\right] \cdot \left[\frac{y}{\sigma_y^3\sqrt{2\pi}} e^{-\frac{y^2}{2\sigma_y^2}}\right]$$

Since the above function could be converted into  $f(x) \cdot f(y)$ , so it's a separable filter.

**2(b)** A Laplacian of Gaussians (LoG) is NOT a separable filter.

The LoG is the sum of the second derivatives of the Gaussian,  $LoG = \frac{\partial^2 G}{\partial x^2} + \frac{\partial^2 G}{\partial y^2}$ , which could not be directly separated into two 1D kernels, thus it is not a separable filter.

**2(c)** We could apply the singular value decomposition (SVD) on this  $3 \times 3$  filter and get  $F = U\Sigma V^\top$ , which as a sum of matrix multiplications, each of a single row/column from the  $U \in \mathbb{R}^{3 \times 3}$  and  $V \in \mathbb{R}^{3 \times 3}$ , multiplied by the diagonal entry from  $\Sigma \in \mathbb{R}^{3 \times 3}$ . The matrix  $\Sigma$  contains entries, which called "singular values", on the diagonal only and they are sorted from the highest to the lowest value. If only one singular value is non-zero, which means that it is a rank 1 matrix and then this filter is separable.

**3** Cross correlation is NOT commutative.

Proof:

By the definition of cross correlation, we have:

$$\text{Corr}[f, g]_t = \text{Corr}[g, f]_{-t}$$

$$\text{which means } f(t) * g(t) = [g(\bar{t}) * f(\bar{t})](-t)$$

but it needs to satisfy  $f(t) * g(t) = g(t) * f(t)$  to be commutative,

so that the cross correlation is not commutative.

**4** Convolve the image with a Gaussian filter with  $\sigma = \sqrt{5}$ 

$$\sigma = \sqrt{\sigma_1^2 + \sigma_2^2} = \sqrt{1^2 + 2^2} = \sqrt{5}$$

Proof:

$$\text{Want to show that } G(x, y|\sigma) = G(x, y|\sqrt{\sigma_1^2 + \sigma_2^2}) = G(x, y|\sigma_1) \cdot G(x, y|\sigma_2)$$

Note that if  $X_1, X_2$  are two independent random variables and  $X_1 \sim N(0, \sigma_1^2 I)$  and  $X_2 \sim N(0, \sigma_2^2 I)$  with two probability density functions  $G_1$  and  $G_2$  respectively, then  $X = X_1 + X_2$  would have a density function  $G = G_1 \cdot G_2$ . And given that  $X \sim N(0, (\sigma_1^2 + \sigma_2^2)I)$ , we have the probability density function (PDF) of variable X:

$$\begin{aligned} f_X(X) &= \frac{1}{2\pi\sqrt{|\Sigma|}} \exp\left\{-\frac{1}{2}X^\top \Sigma^{-1}X\right\} \\ &= \frac{1}{2\pi(\sigma_1^2 + \sigma_2^2)} \exp\left\{-\frac{X^\top X}{2(\sigma_1^2 + \sigma_2^2)}\right\} \\ &= \frac{1}{2\pi(\sigma_1^2 + \sigma_2^2)} \exp\left\{-\frac{x^2 + y^2}{2(\sigma_1^2 + \sigma_2^2)}\right\} \\ &= G(x, y|\sqrt{\sigma_1^2 + \sigma_2^2}) \\ &= G(x, y|\sigma) \end{aligned}$$

where  $|\Sigma| = |(\sigma_1^2 + \sigma_2^2)I| = (\sigma_1^2 + \sigma_2^2)^2$ ,  $X = (x, y)$

Therefore, we've proved that  $\sigma = \sqrt{\sigma_1^2 + \sigma_2^2}$ .

## **2 Coding Part**

### **3 Coding Part Continued**