CS 83: Computer Vision **Winter '23 Year**

Quiz 1 — 2023-01-24

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Credit Statement

I worked on these problems alone, with reference to class notes and the following books:

(i) **Computer Vision: Algorithms and Applications** by **Richard Szeliski**

Problems

Problem 1.

The continuous convolution of two functions $f(x)$ and $g(x)$ is given as

$$(f * g)(x) = \int_{-\infty}^{+\infty} f(y)\, g(x-y)\ \mathrm{d}y.$$

the Gaussian function at scale is defined as

$$G_s(x) = \frac{1}{\sqrt{2\pi s}}\, e^{-\frac{x^2}{2s}},$$

and has the property that

$$\int_{-\infty}^{+\infty} G_s(x)\,\mathrm{d}x = 1.$$

Prove that this class of function satisfies the *semigroup property* — the convolution of one Gaussian function with another produces a third Gaussian function with scale equal to their sum, i.e.

$$(G_{s_1} * G_{s_2})(x) = G_{s_1+s_2}(x).$$

Let

$$G_\alpha(x) = \frac{1}{\sqrt{2\pi\alpha}}\, e^{(-\frac{x^2}{2\alpha})}, \quad G_\beta(x) = \frac{1}{\sqrt{2\pi\beta}}\, e^{(-\frac{x^2}{2\beta})}$$

be Gaussian functions of scale α and β respectively.

Through direct construction, we see that:

$$\begin{aligned}(G_\alpha * G_\beta)(x) &= \int_{-\infty}^{+\infty} G_\alpha(y)\, G_\beta(x-y)\ \mathrm{d}y \\ &= \left(\frac{1}{\sqrt{2\pi\alpha}} \cdot \frac{1}{\sqrt{2\pi\beta}}\right) \int_{-\infty}^{+\infty} e^{\left(-\frac{y^2}{2\alpha}\right)} \cdot e^{\left(-\frac{(x-y)^2}{2\beta}\right)}\ \mathrm{d}y \\ &= \frac{1}{2\pi\sqrt{\alpha\beta}} \int_{-\infty}^{+\infty} e^{-\frac{y^2}{2\alpha} - \frac{(x-y)^2}{2\beta}}\ \mathrm{d}y\end{aligned}$$

By integrating, we get:

$$= \frac{1}{\sqrt{2^3\pi(\alpha+\beta)}} \left[e^{-\frac{x^2}{2(\alpha+\beta)}\, \mathbf{erf}\, \frac{\frac{(\alpha+\beta)y}{\alpha\beta} - x}{\beta\sqrt{\frac{2(\alpha+\beta)}{\alpha\beta}}}} \right]_{-\infty}^{\infty}$$

$\mathbf{erf}\ x$ is an *even* function, and $\mathbf{erf}\ x = 1$ at $x = \infty$.

$$\begin{aligned}&= \frac{1}{\sqrt{2^3\pi(\alpha+\beta)}} \cdot 2e^{-\frac{x^2}{2(\alpha+\beta)}} \\ &= \frac{1}{\sqrt{2\pi(\alpha+\beta)}} \cdot e^{-\frac{x^2}{2(\alpha+\beta)}} \\ &= G_{\alpha+\beta}(x).\end{aligned}$$

Problem 2.

In class, we talked about finite-difference approximation to the derivative of the univariate function $f(x)$. Using Taylor polynomial approximations of $f(x+h)$ and $f(x-h)$, we can easily show that

$$f'(x) = \frac{f(x+h) - f(x-h)}{2h} + O(h2),$$

so that the derivative can be approximated by convolving a discrete version of $f(x)$ — a vector of values $(\ldots, f(x_o - \Delta), f(x_o), f(x_o + \Delta), \ldots)$ with kernel (1/2, 0, -1/2). This is termed a central difference because its interval is symmetric about a sample point.

(i) Derive a higher order central-difference approximation to $f'(x)$ such that the truncation error tends to zero as h^4 instead of h^2. *Hint : consider Taylor polynomial approximations of $f(x \pm 2h)$ in addition to $f(x \pm h)$.* (7 points)

Let c_i denote the coefficient for each term containing h^i in the full Taylor polynomial expansion, then we may write the current estimation of $f'(x)$ as

$$f'(x) = \frac{f(x+h) - f(x-h)}{2h} - \left[c_2h^2 + c_4h^4 + c_6h^6 + \ldots\right]. \tag{0.1}$$

Our goal is to eliminate the h^2 term. Consider the approximations using $f(x \pm 2h)$ by plugging $2h$ into the formula:

$$f'(x) = \frac{f(x+2h) - f(x-2h)}{4h} - \left[4c_2h^2 + 16c_4h^4 + 64c_6h^6 + \ldots\right] \tag{0.2}$$

We notice that the h^2 term in 0.2 is 4 times larger than the h^2 term in 0.1. We can eliminate the h^2 term in $f'(x)$ by subtracting 0.2 from 4 times 0.1:

$$\begin{aligned}
3f'(x) &= 4\frac{f(x+h) - f(x-h)}{2h} - \frac{f(x+2h) - f(x-2h)}{4h} - \left[0h^2 + O(h^4)\right] \\
3f'(x) &= \frac{8\left(f(x+h) - f(x-h)\right) - \left(f(x+2h) - f(x-2h)\right)}{4h} + O(h^4) \\
3f'(x) &= \frac{-f(x+2h) + 8f(x+h) - 8f(x-h) + f(x-2h)}{4h} + O(h^4) \\
f'(x) &= \frac{-f(x+2h) + 8f(x+h) - 8f(x-h) + f(x-2h)}{12h} + O(h^4) \qquad (0.3)
\end{aligned}$$

We get equation 0.3 as a Taylor approximation of $f'(x)$ with a truncation error of $\mathcal{O}(h^4)$.

(ii) What is the corresponding convolution (not correlation!) kernel? (3 points)

The approximation has a correlation kernel of

$$\left(-\frac{1}{12}, \quad \frac{8}{12}, \quad -\frac{8}{12}, \quad \frac{1}{12}\right).$$

The convolution kernel is the same as the correlation kernel, but flipped.

$$\left(\frac{1}{12}, \quad -\frac{8}{12}, \quad \frac{8}{12}, \quad -\frac{1}{12}\right).$$

Problem 3.

In the Rijndael field $F = \mathbb{F}_2[X]/(X^8 + X^4 + X^3 + X + 1)$, where bytes are associated to polynomials modulo $X^8 + X^4 + X^3 + X + 1$, compute the product $01010010 \cdot 10010010 \in F$.

We can represent polynomials in F as binary numbers, where the state of each bit (whether 0 or 1) represents whether the corresponding power in the polynomial has a factor of 0 or 1.

Then:

$$X^8 + X^4 + X^3 + X + 1 = 100011011$$

Then, we can perform the multiplication modulo 2:

$$\begin{array}{r}
1\ 0\ 0\ 1\ 0\ 0\ 1\ 0 \\
1\ 0\ 1\ 0\ 0\ 1\ 0 \\
\times 1\ 0\ 0\ 1\ 0\ 0\ 1\ 0\ \cdot \\
\hline
1\ 0\ 0\ 1\ 0\ 0\ 1\ 0\ \cdot\ \cdot\ \cdot\ \cdot \\
1\ 0\ 0\ 1\ 0\ 0\ 1\ 0\ \cdot\ \cdot\ \cdot\ \cdot\ \cdot\ \cdot \\
\hline
1\ 0\ 1\ 1\ 0\ 2\ 1\ 0\ 2\ 0\ 0\ 1\ 0\ 0
\end{array}$$

Shifting back to base 2, we get: 10110010000100

We then need to find this number $\mod 100011011$

$$\begin{array}{r|r}
\multicolumn{2}{c}{\mod 10110010000100, 100011011} \\
100011011 & 10110010000100 \\
100000 & 100011011\ .\ .\ .\ .\ . \\
 & 111111100\ .\ .\ . \\
1000 & 100011011\ .\ .\ . \\
 & 111001111\ .\ . \\
100 & 100011011\ .\ . \\
 & 110101000\ . \\
10 & 100011011\ . \\
 & 101100110 \\
1 & 100011011 \\
\hline
101111 & 1111101
\end{array}$$

Thus, the product in F is 1111101