

Lecture 12 Sample Problem Solutions

Problem 12.1

1. If we apply the inverse 2D DTFT formula,

$$h[n_1, n_2] = \frac{1}{(2\pi)^2} \int_{-\pi}^{\pi} \int_{-\pi}^{\pi} H(\omega_1, \omega_2) e^{j\omega_1 n_1} e^{j\omega_2 n_2} d\omega_1 d\omega_2$$

We get that

$$h[n_1, n_2] = \left(\frac{1}{5} \operatorname{sinc} \left(\frac{\pi n_1}{5} \right) \right) \left(\frac{1}{3} \operatorname{sinc} \left(\frac{\pi n_2}{3} \right) \right)$$

for all $-\infty < n_1 < \infty$ and $-\infty < n_2 < \infty$.

2. The standard way to implement 2D convolution is

$$f[n_1, n_2] = \sum_{m_1=-\infty}^{\infty} \sum_{m_2=-\infty}^{\infty} x[m_1, m_2] h[n_1 - m_1, n_2 - m_2] \quad (12.1-1)$$

Eq. 12.1-1 requires a double-summation, with $N_1 N_2$ terms, in order to compute each output pixel. There are $(N_1 + M_1 - 1) \times (N_2 + M_2 - 1) = \mathcal{O}\{N_1 N_2\}$ output pixels. So the total complexity is $\mathcal{O}\{(N_1 N_2)^2\}$.

More loosely, if $N_1 \approx N_2 \approx N$, then we can say that standard convolution has a complexity of $\mathcal{O}\{N^4\}$.

3. The filter $h[n_1, n_2]$ is separable, so we can filter the rows first, and then the columns:

$$f[n_1, n_2] = \sum_{m_1=-\infty}^{\infty} \left(\sum_{m_2=-\infty}^{\infty} x[m_1, m_2] h_2[n_2 - m_2] \right) h_1[n_1 - m_1] \quad (12.1-2)$$

where

$$h_1[n_1] = \left(\frac{1}{5} \operatorname{sinc} \left(\frac{\pi n_1}{5} \right) \right), \quad h_2[n_2] = \left(\frac{1}{3} \operatorname{sinc} \left(\frac{\pi n_2}{3} \right) \right)$$

Eq. 12.1-2 does the row-convolution first, requiring N_2 operations per pixel. Then it does the column-convolution, requiring N_1 operations per pixel. If there are $\mathcal{O}\{N_1 N_2\}$ pixels, then the complexity is $\mathcal{O}\{N_1 N_2 (N_1 + N_2)\}$.

Problem 12.2

Let's assume that the spectrum of $u[n]$ is

$$U(\omega) = \frac{1}{|\omega|}$$

for $|\omega| < \pi$. After filtering with an ideal anti-aliasing filter, it is

$$V(\omega) = \begin{cases} \frac{1}{|\omega|} & |\omega| \leq \frac{\pi}{2} \\ 0 & \text{otherwise} \end{cases}$$

After downsampling, we get

$$X(\omega) = \frac{1}{2} \sum_{k=0}^1 V\left(\frac{\omega - 2\pi k}{2}\right) = \frac{1}{2|\omega/2|} = \frac{1}{|\omega|}$$

After upsampling,

$$Y(\omega) = X(2\omega) = \begin{cases} \frac{1}{2|\omega|} & |\omega| \leq \frac{\pi}{2} \\ \frac{1}{2(\pi-|\omega|)} & \frac{\pi}{2} \leq |\omega| \leq \pi \end{cases}$$

1. If $h_a[n] = \frac{\sin(\pi n/2)}{\pi n/2}$, then

$$H_a(\omega) = \begin{cases} 2 & |\omega| \leq \frac{\pi}{2} \\ 0 & \text{otherwise} \end{cases}$$

So

$$Z(\omega) = H_a(\omega)Y(\omega) = \begin{cases} \frac{1}{|\omega|} & |\omega| \leq \frac{\pi}{2} \\ 0 & \frac{\pi}{2} \leq |\omega| \leq \pi \end{cases}$$

Which is exactly equal to $U(\omega)$ for $|\omega| \leq \pi/2$, and exactly equal to zero at higher frequencies.

2. If $h_b[n] = (h_a[n])^2$, then

$$H_b(\omega) = \frac{1}{2\pi} H_a(\omega) \otimes H_a(\omega) = 2 \left(\frac{\pi - |\omega|}{\pi} \right)$$

and therefore

$$Z(\omega) = H_b(\omega)Y(\omega) = \begin{cases} \frac{(\pi-|\omega|)/\pi}{|\omega|} & |\omega| \leq \frac{\pi}{2} \\ \frac{1}{\pi} & \frac{\pi}{2} \leq |\omega| \leq \pi \end{cases}$$

which is slightly less than $U(\omega)$ at low frequencies ($(\pi - |\omega|)/\pi$ times less), but then slightly higher than $U(\omega)$ at high frequencies (π/ω times higher). Actually, the spectral shape in general is closer to the spectral shape of $U(\omega)$, so that, even though the high frequencies are entirely constructed from aliasing, it is still often true that this version of $Z(\omega)$ is a better-looking image than the ideal band-limited version.

An even better interpolating filter can be constructed using a two-part interpolator, $H_c(\omega)$, which has one type of spectrum below $\pi/2$, and a different nonzero type of spectrum at high frequencies.

An even better solution is to estimate the high frequencies using a nonlinear regression algorithm, e.g., a neural net trained to estimate the high-frequency component of $U(\omega)$ given its low-frequency component.