

CS 4442 Assignment 3 Report

Problem 1 – Proof of separable convolution for the Gaussian kernel

$$y[m,n] = x[m,n] * h[m,n] = \sum_{j=-\infty}^{\infty} \sum_{i=-\infty}^{\infty} x[i,j] \cdot h[m-i, n-j] \quad // \text{By 2D definition of Convolution}$$

$$y[m,n] = h[m,n] * x[m,n] = \sum_{j=-\infty}^{\infty} \sum_{i=-\infty}^{\infty} h[i,j] \cdot x[m-i, n-j] \quad // \text{Commutative law since convolution is commutative}$$

If $h[m,n]$ is separable to $(M \times 1)$ and $(1 \times N)$, then $h[m,n] = h_1[m] \cdot h_2[n]$.

In the case of the Gaussian Kernel, assuming the matrix size is a $(2K+1) \times (2K+1)$, it can be separated into a $M \times 1$ column vector and a $1 \times N$ row vector (1D).

I.e.

$$\begin{matrix} \text{Gaussian Matrix} \\ \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} \end{matrix} = \begin{matrix} M \times 1 \\ \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \end{matrix} \times \begin{matrix} 1 \times N \\ \begin{bmatrix} 1 & 2 & 1 \end{bmatrix} \end{matrix}$$

Column Vector Row Vector

$$G_{\sigma}(x,y) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x^2+y^2)}{2\sigma^2}\right)$$

Thus,

$$\begin{aligned} y[m,n] &= h[m,n] * x[m,n] = \sum_{j=-\infty}^{\infty} \sum_{i=-\infty}^{\infty} h[i,j] \cdot x[m-i, n-j] \\ &= \sum_{j=-\infty}^{\infty} \sum_{i=-\infty}^{\infty} h_1[i] \cdot h_2[j] \cdot x[m-i, n-j] \\ &= \sum_{j=-\infty}^{\infty} h_2[j] \left(\sum_{i=-\infty}^{\infty} h_1[i] \cdot x[m-i, n-j] \right) \end{aligned}$$

Since the definition of 1D convolution is:

$$y[n] = x[n] * h[n] = \sum_{k=-\infty}^{\infty} x[k] \cdot h[n-k]$$

It convolves with input and h_1 , then convolves once again with the result of the previous convolution and h_2 . Therefore, separable 2D convolution performs twice the 1D convolution in horizontal and vertical direction.

Thus, since the Gaussian Kernel can be separated into $(M \times 1)$ and $(1 \times N)$ vectors, it is a spatially separable convolution.

Problem 1 – Is the Sobel kernel spatially separable?

Sobel Kernel

$$\begin{matrix} \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \\ S_x \end{matrix} = \begin{matrix} \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \\ \text{Column Vector} \end{matrix} \times \begin{matrix} \begin{bmatrix} -1 & 0 & 1 \end{bmatrix} \\ \text{Row Vector} \end{matrix}$$

$$\begin{matrix} \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \\ S_y \end{matrix} = \begin{matrix} \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} \\ \text{Column Vector} \end{matrix} \times \begin{matrix} \begin{bmatrix} 1 & 2 & 1 \end{bmatrix} \\ \text{Row Vector} \end{matrix}$$

The Sobel Kernel is spatially separable since it can be decomposed into a $(M \times 1)$ and $(1 \times N)$ vectors. \therefore Spatially separable convolution can be performed.

Problem 2 – Edge Detection

*See Jupyter Notebook for solution code

Original Image



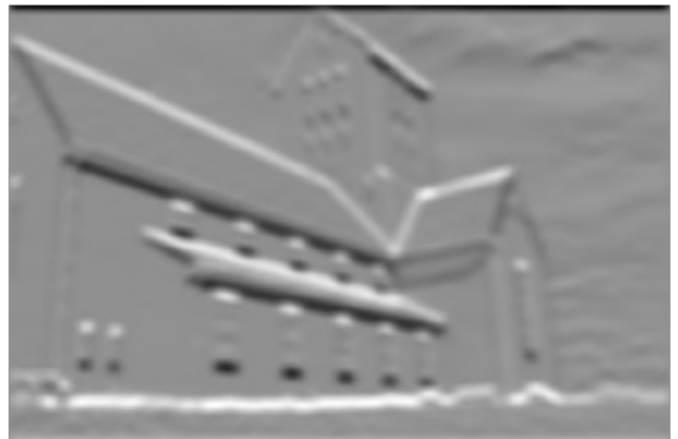
Gaussian Smoothing sigma=1



Derivative wrt Y



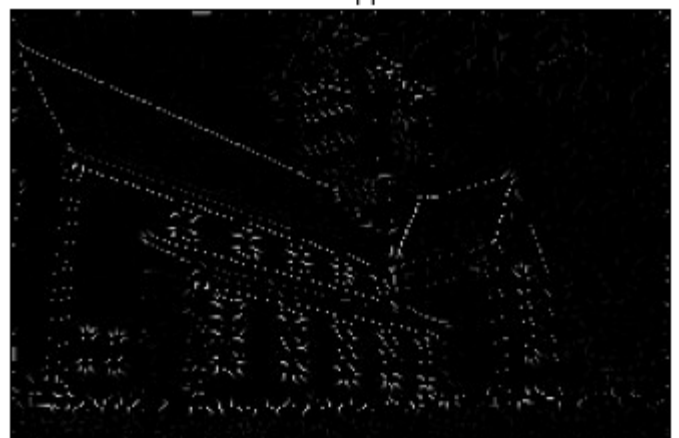
Derivative wrt X



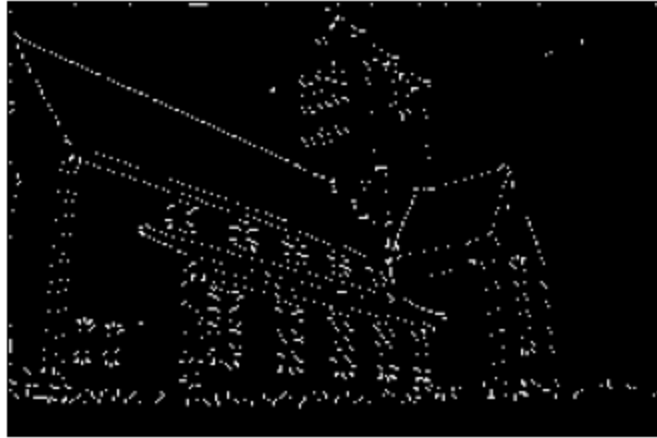
Gradient Intensity



Non-Max Suppression



Binary Threshold Hysteresis:low=40 high=50



Problem 3 – Corner Detection

*See Jupyter Notebook for solution code

Corners Found



Corners (threshold=0.1)

