

Local Structure - assignment 4

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1 Introduction

In this exercise we implement a few exercises with the goal to learn the effect of Gaussian derivatives as part of a convolution. Using this, we will finally implement the ‘Canny Edge Detector’.

2 Analytical Local Structure

As starter for this assignment, we need to calculate a number of derivatives of the given function, $f(x, y) = A \sin(Vx) + B \cos(Wy)$.

$$\begin{aligned}f_x &= \frac{\delta f}{\delta x} \\f_x &= A \frac{\delta}{\delta x} \sin(Vx) + B \frac{\delta}{\delta x} \cos(Wy) \\f_x &= A \cos(Vx) * V + B * 0 = AV \cos(Vx)\end{aligned}$$

$$\begin{aligned}f_y &= \frac{\delta f}{\delta y} \\f_y &= A \frac{\delta}{\delta y} \sin(Vx) + B \frac{\delta}{\delta y} \cos(Wy) \\f_y &= A * 0 - B \sin(Wy) * W = -BW \sin(Wy)\end{aligned}$$

$$\begin{aligned}f_{xx} &= \frac{\delta f_x}{\delta x} \\f_{xx} &= AV \frac{\delta}{\delta x} \cos(Vx) \\f_{xx} &= -AV^2 \sin(Vx)\end{aligned}$$

$$\begin{aligned}f_{xy} &= \frac{\delta f_x}{\delta y} \\f_{xy} &= AV \frac{\delta}{\delta y} \cos(Vx) = 0\end{aligned}$$

$$\begin{aligned}f_{yy} &= \frac{\delta f_y}{\delta y} \\f_{yy} &= -BW \frac{\delta}{\delta y} \sin(Wy) \\f_{yy} &= -BW^2 \cos(Wy)\end{aligned}$$

The second part of this first assignment asks us to complete the given code, which creates a visualization of f_x and f_y . After that, we apply a quiver plot to the visualization of f , for which code was provided. This gives us the following image:

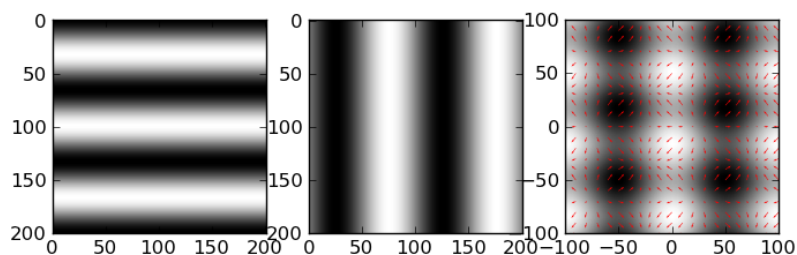


Figure 1: Visualization of f_x , f_y and a quiverplot of f

3 Gaussian Convolution

To perform a Gaussian convolution, we need to make a Gauss filter. To do this, we use the Gaussian function. For this part of the exercise, we use the 2 dimensional Gaussian function, which is:

$$\frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

To create the filter, we apply this to each (x, y) in a grid of size $(6s + 1) \times (6s + 1)$.

We can visualize this so-called *kernel* in 3D. This gives us the following image:

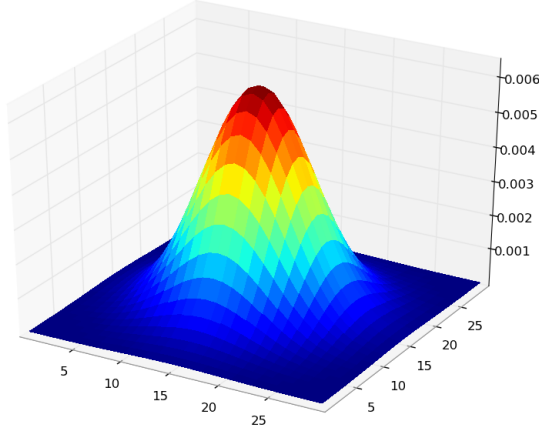


Figure 2: Kernel of Gaussian filter for $s = 5$

The complexity of this operation in s is of order $\mathcal{O}(s^2)$. This is because the program runs two loops, each over $(6s + 1)$. One of these loops is inside the other, since we loop over the filter of size $(6s + 1) \times (6s + 1)$. This means that we have a total of $(6s + 1) * (6s + 1)$ iterations, which leads to a total of $36s^2 + 12s + 1$ iterations, which is of the order $\mathcal{O}(s^2)$. This can also be seen in the following graph which plots the execution time versus the size of s . This is obviously exponential:

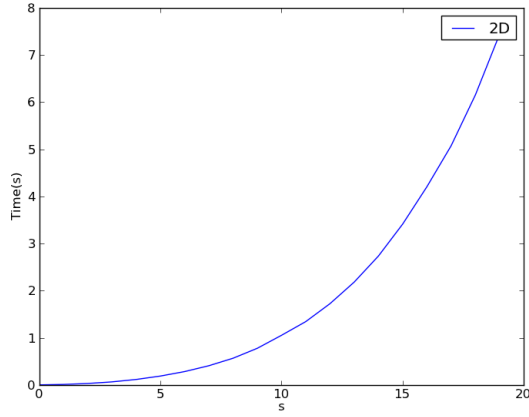


Figure 3: Two dimensional Gaussian convolution

4 Separable Gaussian Convolution

A performance increase for the Gaussian Convolution can be gained by applying the convolution first in one direction and then in the second. This way, we only have to calculate once in the x-direction and once in the y-direction of the filter,

instead of for each x and y.

That this is possible can be seen in the following proof:

$$\frac{\delta}{\delta x} \frac{\delta}{\delta y} G_{2D} = \frac{\delta}{\delta x} \left(\frac{\delta}{\delta x} (G_{1D}(x) * G_{1D}(y)) \right) = \frac{\delta}{\delta x} (G_{1D}(x) * \frac{\delta}{\delta y} G_{1D}(y)) = \frac{\delta}{\delta x} G_{1D}(x) * \frac{\delta}{\delta y} G_{1D}(y)$$

This means that for each s the order $\mathcal{O}(s)$. This is because the Gaussian function has to be applied n times per direction, with $n = \text{ceil}(6s + 1)$. This means that the total times the Gaussian function has to be applied is $2 * (6s + 1) = 12s + 2$. This is in the order $\mathcal{O}(s)$.

If we plot the timings, this can be seen as well, the line is a straight line.

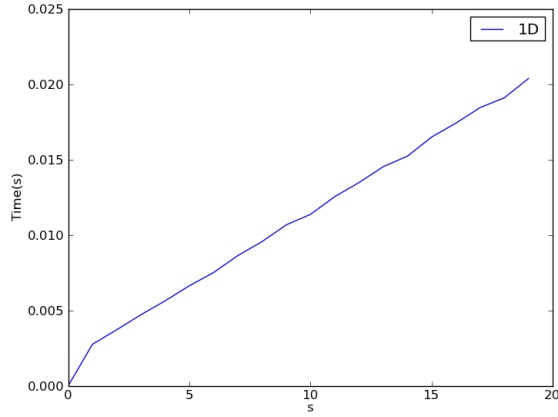


Figure 4: One-dimensional Gaussian convolution

5 Gaussian Derivatives

The Gaussian derivative of an image is the image that is obtained by convolving the image with a derivative of the Gaussian function. To do this, first we will need the first and second derivative of the one-dimensional Gaussian function. These are as follows:

$$f'(x) = \frac{1}{2\pi s^4} * (-x e^{-\frac{x^2}{2s^2}})$$

$$f''(x) = \frac{1}{2\pi s^6} * (-x^2 - s^2) * e^{-\frac{x^2}{2s^2}}$$

We can apply these functions in different levels on the image, creating a so-called ‘2-jet’:

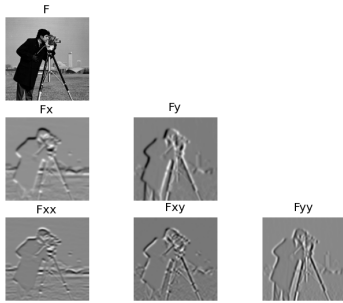


Figure 5: 2-Jet

6 Canny Edge Detector

The final exercise was to implement the Canny Edge Detector. In the assignment we were said to check in a 3x3 neighbourhood for both negative and positive sides on either side of the pixel. However, this did not work properly for us. Instead, we implemented the detector as described on <http://suraj.lums.edu.pk/~cs436a02/CannyImplementation.htm>, which includes the use of a non-maximum suppression step, where you find the 'core' of a line by checking the surrounding pixels in the direction that is perpendicular to the line, and hysteresis thresholding, where you follow the line to see what points are noise and what points are actually part of the line. This gives us the following result:

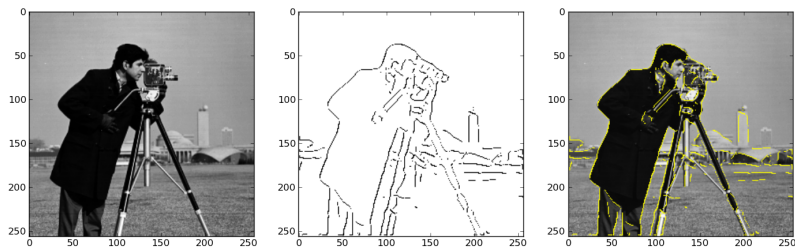


Figure 6: Canny Edge Detector