Gaussian Kernel

The Gaussian kernel is defined as:

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

Where:

- x and y are the distances from the center of the kernel,
- σ is the standard deviation, and
- $G(x, y)$ is the value of the Gaussian function at point (x, y).

Table-1: 5x5 Gaussian Kernel table

Kernel	Formatted Kernel
[0.00291502 0.01306423 0.02153928 0.01306423 0.00291502] [0.01306423 0.05854983 0.09653235 0.05854983 0.01306423] [0.02153928 0.09653235 0.15915494 0.09653235 0.02153928] [0.01306423 0.05854983 0.09653235 0.05854983 0.01306423] [0.00291502 0.01306423 0.02153928 0.01306423 0.00291502]	[[1 4 7 4 1] [4 20 33 20 4] [7 33 54 33 7] [4 20 33 20 4] [1 4 7 4 1]]

Practical Experiment:

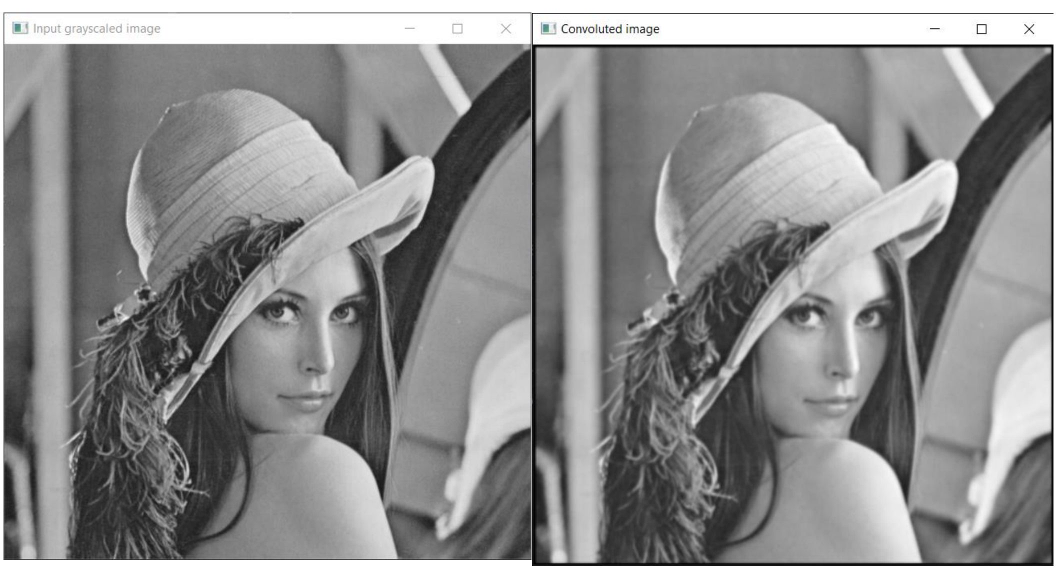

Fig-1: Input grayscaled image and output convoluted image(gaussian)

Mean Kernel

Mathematically, the mean kernel is defined as a matrix of equal weights:

Table-2: 3x3 Mean Kernel Table

Kernel	Formatted Kernel
[0.11111111 0.11111111 0.11111111] [0.11111111 0.11111111 0.11111111] [0.11111111 0.11111111 0.11111111]	[1. 1. 1.] [1. 1. 1.] [1. 1. 1.]

Practical Experiment:

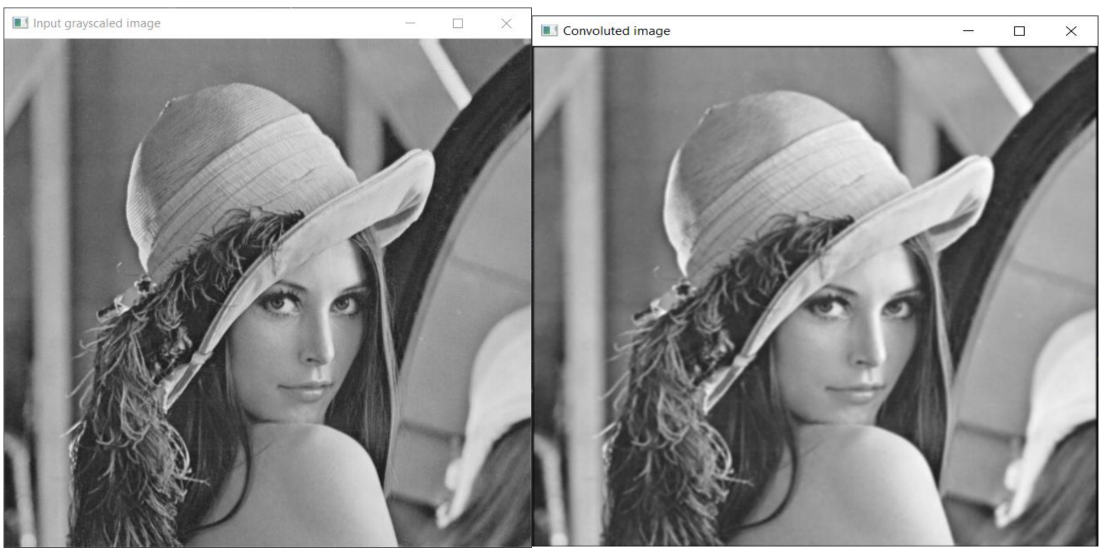

Fig-2: Input grayscaled image and output convoluted image(mean)

Laplacian kernel

Mathematically, Laplacian filter is defined as:

$$\Delta^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

Table-3: 3x3 Center positive Laplacian kernel Table

Kernel	Formatted Kernel
[[-1 -1 -1] [-1 8 -1] [-1 -1 -1]]	[[-1 -1 -1] [-1 8 -1] [-1 -1 -1]]

Practical Experiment:

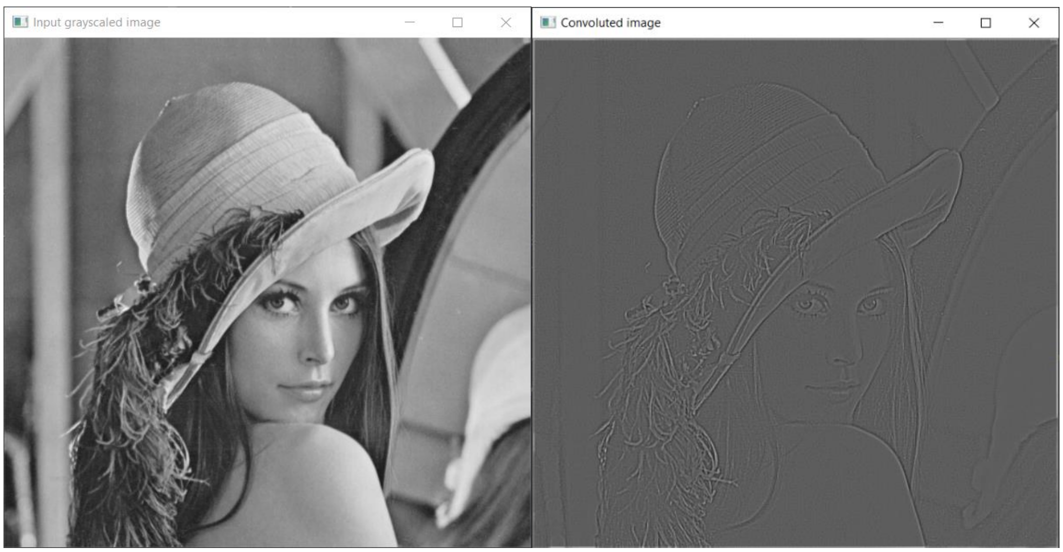

Fig-3: Input grayscaled image and output convoluted image(Laplacian center positive kernel)

Table-4: 3x3 Center negative Laplacian kernel Table

Kernel	Formatted Kernel
[1 1 1] [1 -8 1] [1 1 1]	[1 1 1] [1 -8 1] [1 1 1]

Practical Experiment:

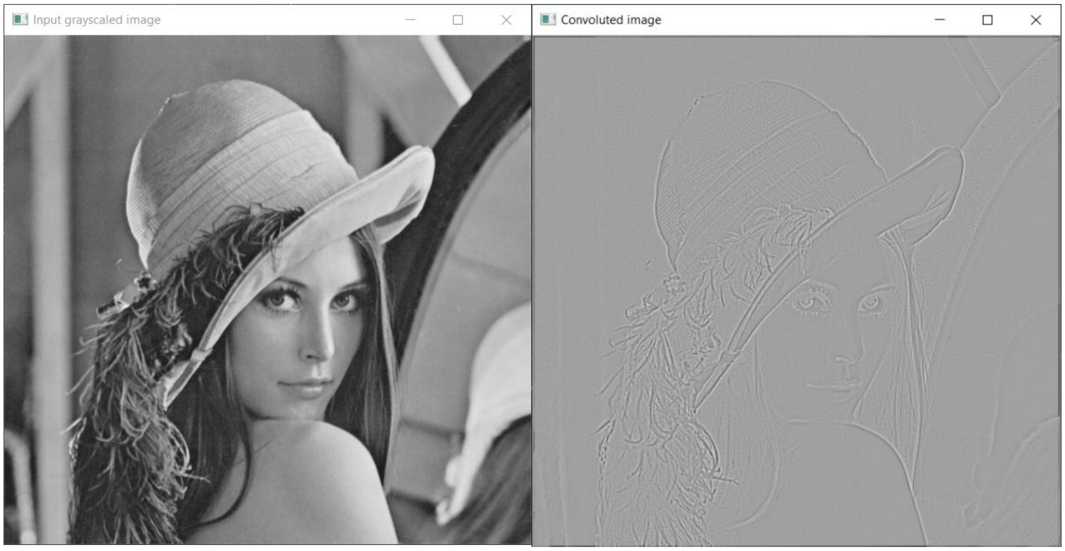

Fig-4: Input grayscaled image and output convoluted image(Laplacian center negative kernel)

LOG Kernel:

Mathematically, the LoG kernel is defined as the Laplacian of the Gaussian function:

$$LoG(x,y) = \frac{1}{\pi\sigma^4}\left(1 - \frac{x^2+y^2}{2\sigma^2}\right)e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Where:

- (x, y) are the spatial coordinates.
- σ is the standard deviation of the Gaussian function, controlling the amount of smoothing.
- $LoG(x, y)$ represents the value of the LoG kernel at coordinates (x, y).

Practical Experiment:

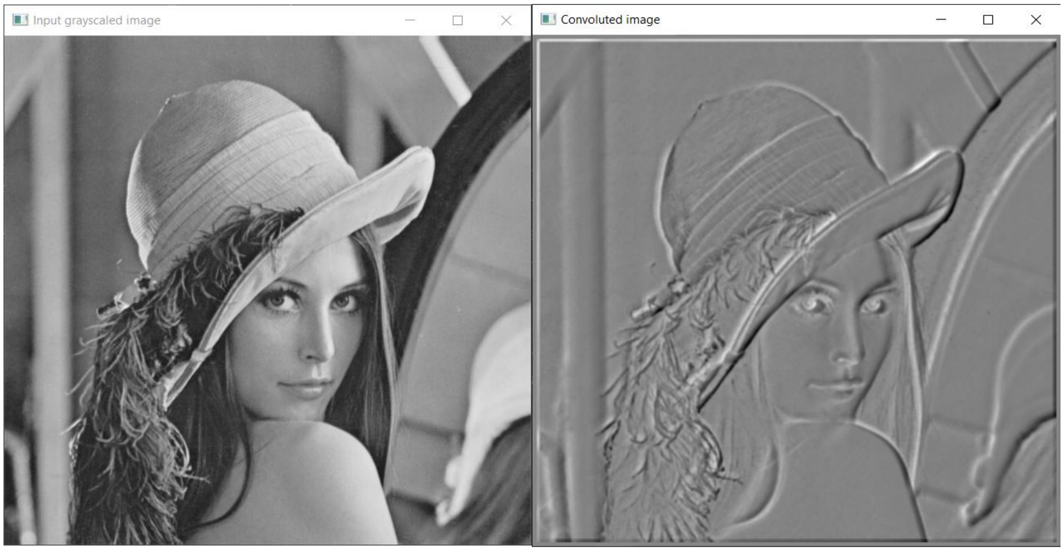

Fig-5: Input grayscaled image and output convoluted image(LoG kernel)

Sobel kernel

Horizontal Sobel Kernel	Vertical Sobel kernel
|-1 -2 -1 | | 0 0 0 | | 1 2 1 |	| -1 0 1 | | -2 0 2 | | -1 0 1 |

To compute the gradient magnitude, the horizontal and vertical gradients are convolved with the image using these kernels separately, and then combined using the following formula:

$$G = \sqrt{(G_x)^2 + (G_y)^2}$$

Where:

- G is the gradient magnitude.
- G_x is the horizontal gradient.
- G_y is the vertical gradient.

Practical Experiment:

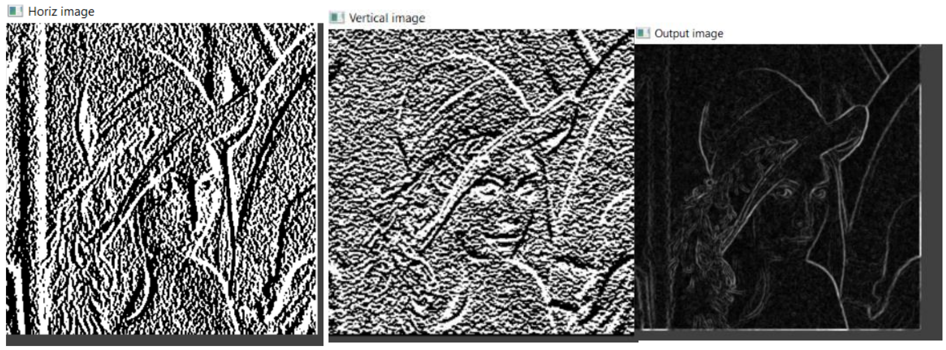

Fig-6: Horizontal, Vertical and output convoluted image(Sobel kernel)

Operation Type: HSV & RGB Difference

Fig-7: Original RGB image and output convoluted image

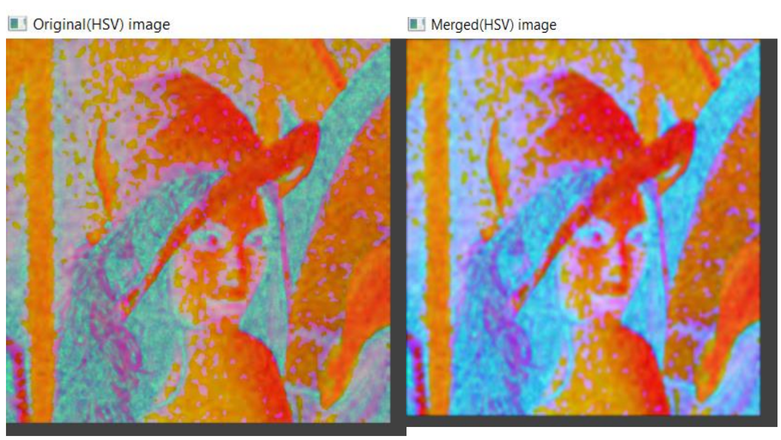

Fig-8: Original RGB image and output convoluted image

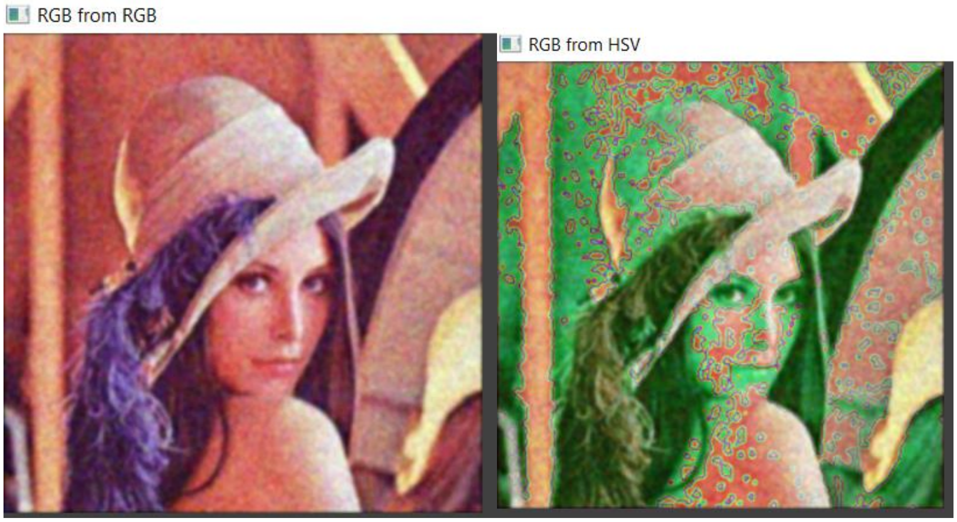

Fig-8: RGB convoluted image and HSV to RGB convoluted image

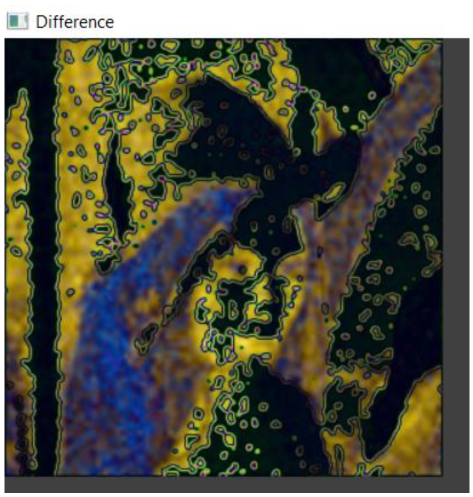

Fig-9: Difference between RGB convoluted image and HSV to RGB convoluted image