Gaussian Kernel

- Formula:

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

Where:

- ullet x and y are the distances from the center of the kernel,
- ullet σ is the standard deviation, and
- * G(x,y) is the value of the Gaussian function at point (x,y).
- Sample kernel (5x5)

Kernel	Formatted Kernel				
[0.00291502 0.0130642 0.02153923 0.0130642 0.00291502]	[[1	4	7	4	1]
[0.0130642 0.05854969 0.09653213 0.05854969 0.0130642]	[4	20	33	20	4]
[0.02153923 0.09653213 0.15915457 0.09653213 0.02153923]	[7	33	54	33	7]
[0.0130642 0.05854969 0.09653213 0.05854969 0.0130642]	[4	20	33	20	4]
[0.00291502 0.0130642 0.02153923 0.0130642 0.00291502]]	[1	4	7	4	1]]

- Input and Output:

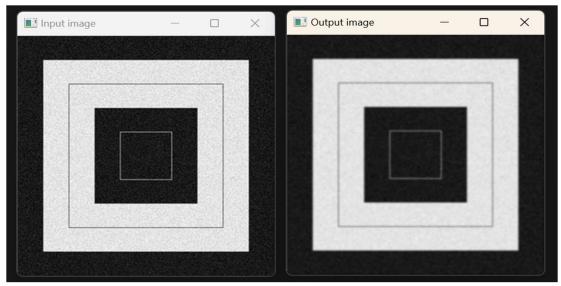


Fig-1: Gaussian (7x7) with sigmaX=1, sigmaY=1 and center=(3,3)

Mean Kernel

- It is a matrix having equal weight at each cell.
- Sample kernel (5x5)

Kernel	Formatted Kernel
[[0.04 0.04 0.04 0.04 0.04]	[[1. 1. 1. 1. 1.]
[0.04 0.04 0.04 0.04 0.04]	[1. 1. 1. 1. 1.]
[0.04 0.04 0.04 0.04 0.04]	[1. 1. 1. 1. 1.]
[0.04 0.04 0.04 0.04 0.04]	[1. 1. 1. 1. 1.]
[0.04 0.04 0.04 0.04 0.04]]	[1. 1. 1. 1. 1.]]

Table-2: Mean Kernel Table (5x5)

- Input and Output

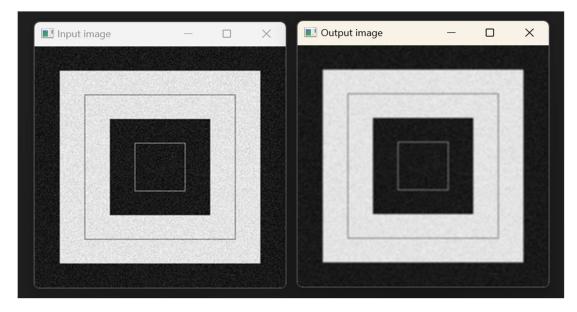


Fig-2: Mean kernel of size (3x3) and center=(1,1)

Laplacian kernel

- Formula

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

- Sample kernel (3 x 3)

- Input and Output:

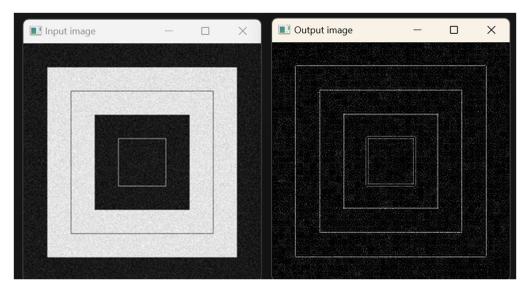


Fig-3: Laplacian kernel of size (3x3) and center=(1,1)

LOG Kernel:

- Formula

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

Where:

- $^{ullet}\left(x,y\right)$ are the spatial coordinates.
- ullet 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).

- Sample kernel (9x9)

```
[[ 1 4 12 21 25 21 12 4 1]
[ 4 17 41 59 63 59 41 17 4]
[ 12 41 66 37 3 37 66 41 12]
[ 21 59 37 -144 -282 -144 37 59 21]
[ 25 63 3 -282 -489 -282 3 63 25]
[ 21 59 37 -144 -282 -144 37 59 21]
[ 12 41 66 37 3 37 66 41 12]
[ 4 17 41 59 63 59 41 17 4]
[ 1 4 12 21 25 21 12 4 1]]
```

- Input and Output

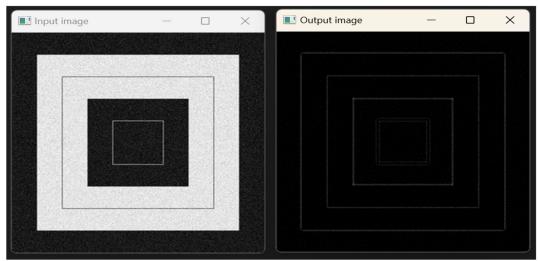


Fig-4: LoG kernel of size (9x9) and center=(4,4)

Sobel kernel

- It is used for detecting edges.
- Sample kernel (3x3)

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

- Two convolution is performed, then result is generated from them using

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

Where:

- ullet G is the gradient magnitude.
- ullet G_x is the horizontal gradient.
- ullet G_y is the vertical gradient.
- Input and Output

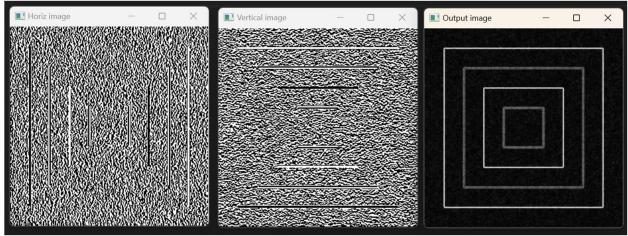


Fig-5: Two Sobel kernel of size (3x3) and center=(1,1)

Operation Type: HSV & RGB Difference

Using (7x7) Gaussian kernel, sigmaX=1, sigmaY=1, center = (3,3)

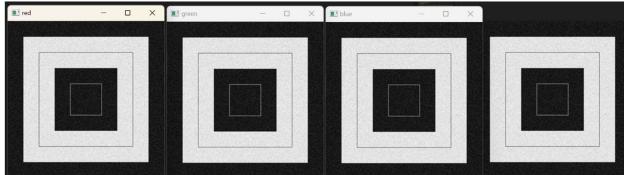


Fig-6: red, green, blue channel and input

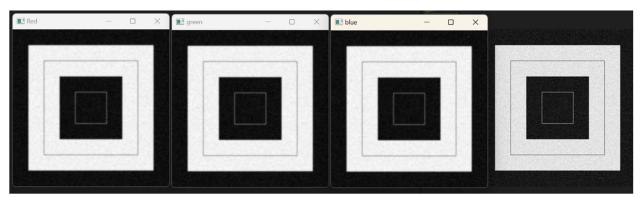


Fig-7: Convoluted red, green, blue channel and input

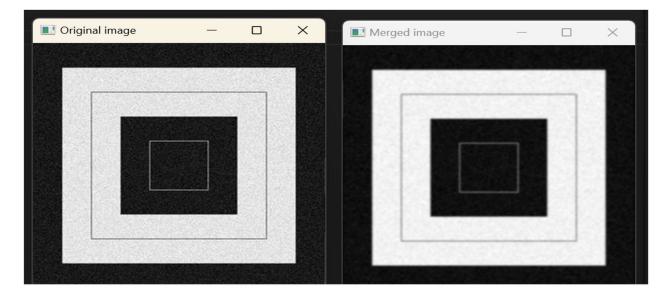


Fig-8: Original and merged convoluted image

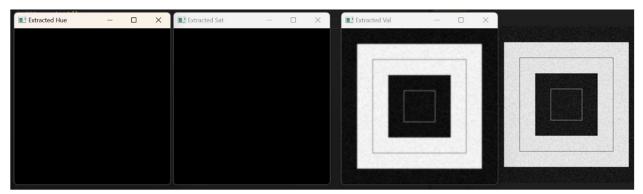


Fig-9: h, s, v channel with input

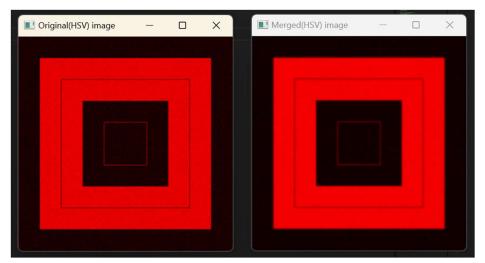


Fig-10: Original and merged convoluted HSV

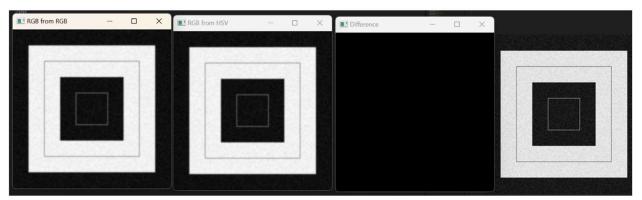


Fig-11: Difference between two convoluted images

RGB and HSV difference using Mean kernel of (3x3) center=(1,1)

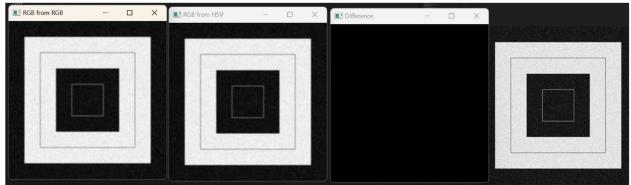


Fig-12: Difference between two convoluted images

- RGB and HSV difference using Laplacian kernel of (3x3) center=negative

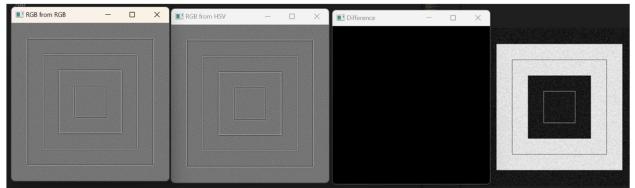


Fig-13: Difference between two convoluted images

- RGB and HSV difference using Log kernel of (3x3) sigma=1, center = (1,1)

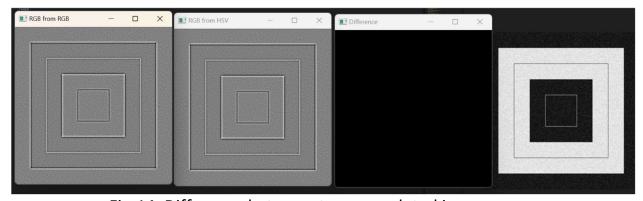


Fig-14: Difference between two convoluted images

- RGB and HSV difference using Soble kernel of (3x3)

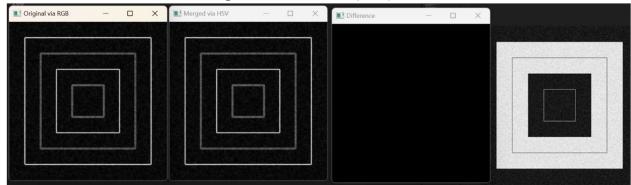


Fig-15: Difference between two convoluted images

RGB and HSV difference sing (7x7) Gaussian kernel, sigmaX=1, sigmaY=1,
 center = (3,3)

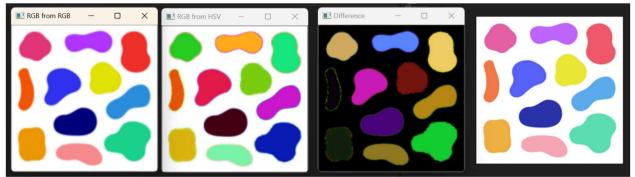


Fig-16: Difference between two convoluted image

- Edge detection using Sobel

