A Developer Diary

{about:"code learn and share"}

May 19, 2019 By Abhisek Jana — 6 Comments (Edit)

Applying Gaussian Smoothing to an Image using Python from scratch

Gaussian Smoothing

Using Gaussian filter/kernel to smooth/blur an image is a very important tool in Computer Vision. You will find many algorithms using it before actually processing the image. Today we will be Applying Gaussian Smoothing to an image using Python from scratch and not using library like OpenCV.

High Level Steps:

There are two steps to this process:

- Create a Gaussian Kernel/Filter
- Perform Convolution and Average

Gaussian Kernel/Filter:

Create a function named `gaussian_kernel()`, which takes mainly two parameters. The size of the kernel and the standard deviation.

```
def gaussian_kernel(size, sigma=1, verbose=False):

    kernel_1D = np.linspace(-(size // 2), size // 2,
size)
```

```
    for i in range(size):
        kernel_1D[i] = dnorm(kernel_1D[i], 0, sigma)
    kernel_2D = np.outer(kernel_1D.T, kernel_1D.T)

    kernel_2D *= 1.0 / kernel_2D.max()

    if verbose:
        plt.imshow(kernel_2D,
interpolation='none',cmap='gray')
        plt.title("Image")
        plt.show()

    return kernel_2D
```

Create a vector of equally spaced number using the size argument passed. When the `size = 5`, the `kernel_1D` will be like the following:

```
array([-2., -1.,  0.,  1.,  2.])
```

Now we will call the `dnorm()` function which returns the density using the `mean = 0` and standard deviation. We will see the function definition later. The `kernel_1D` vector will look like:

```
array([0.05399097, 0.24197072, 0.39894228, 0.24197072,
0.05399097])
```

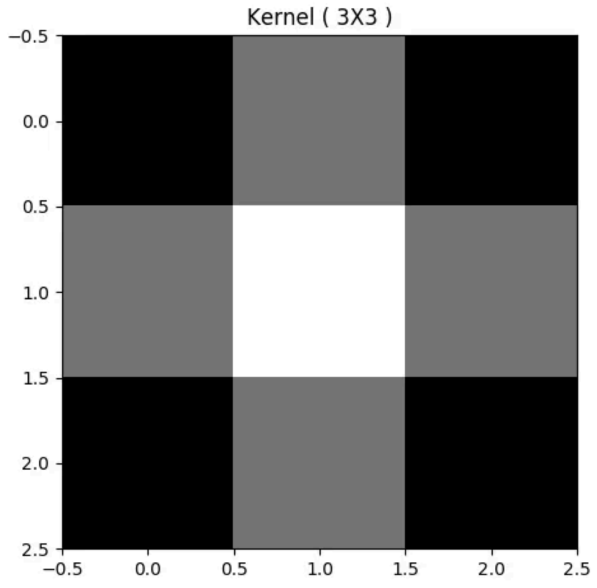
Then we will create the outer product and normalize to make sure the center value is always 1.

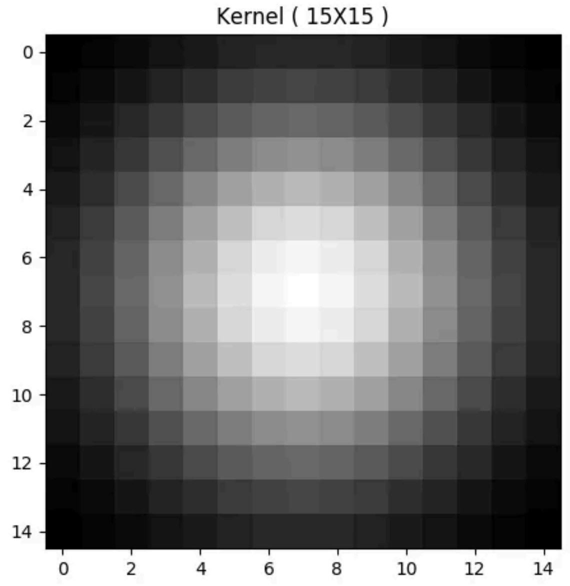
Kernel Output:

In order to set the sigma automatically, we will use following equation: (This will work for our purpose, where filter size is between 3-21):

```
sigma=math.sqrt(kernel_size)
```

Here is the output of different kernel sizes.





As you are seeing the `sigma` value was automatically set, which worked nicely. This simple trick will save you time to find the sigma for different settings.

dnorm()

```
def dnorm(x, mu, sd):
    return 1 / (np.sqrt(2 * np.pi) * sd) * np.e ** (-
np.power((x - mu) / sd, 2) / 2)
```

Here is the `dorm()` function. Just calculated the density using the formula of `Univariate Normal Distribution`.

Convolution and Average:

We will create the convolution function in a generic way so that we can use it for other operations. This is not the most efficient way of writing a convolution function, you can always replace with one provided by a library. However the main objective is to perform all the basic operations from scratch.

I am not going to go detail on the `Convolution` (or `Cross-Correlation`) operation, since there are many fantastic tutorials available already. Here we will only focus on the implementation.

Let's look at the `convolution()` function part by part.

```
def convolution(image, kernel, average=False,
verbose=False):

    if len(image.shape) == 3:
        print("Found 3 Channels :
{}".format(image.shape))
        image = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
        print("Converted to Gray Channel. Size :
{}".format(image.shape))
    else:
        print("Image Shape : {}".format(image.shape))

    print("Kernel Shape : {}".format(kernel.shape))

    if verbose:
        plt.imshow(image, cmap='gray')
        plt.title("Image")
        plt.show()
```

The function has the image and kernel as the required parameters and we will also pass average as the 3rd argument. The average argument will be used only for smoothing filter. Notice, we can actually pass any filter/kernel, hence this function is not coupled/depended on the previously written `gaussian_kernel()` function.

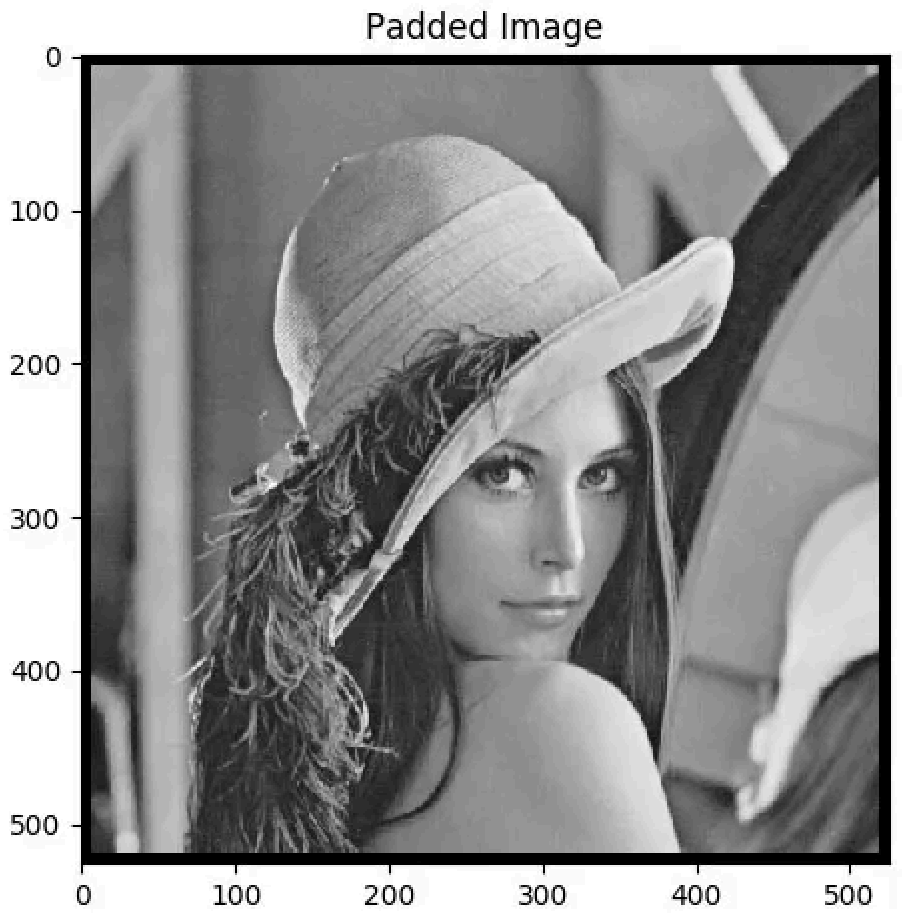
Since our `convolution()` function only works on image with single channel, we will convert the image to gray scale in case we find the image has 3 channels (Color Image). Then plot the gray scale image using `matplotlib`.

```
image_row, image_col = image.shape
kernel_row, kernel_col = kernel.shape

output = np.zeros(image.shape)

pad_height = int((kernel_row - 1) / 2)
pad_width = int((kernel_col - 1) / 2)

padded_image = np.zeros((image_row + (2 * pad_height),
image_col + (2 * pad_width)))

padded_image[pad_height:padded_image.shape[0] -
pad_height, pad_width:padded_image.shape[1] - pad_width]
= image
```

We want the output image to have the same dimension as the input image. This is technically known as the `“same convolution”`. In order to do so we need to pad the image. Here we will use `zero padding`, we will talk about other types of padding later in the tutorial. Now for `“same convolution”` we need to calculate the size of the padding using the following formula, where `k` is the size of the kernel.

$$\frac{(k-1)}{2}$$

In the the last two lines, we are basically creating an empty numpy 2D array and then copying the image to the proper location so that we can have the padding applied in the final output. In the below image we have applied a padding of 7, hence you can see the black border.



```
for row in range(image_row):
    for col in range(image_col):
        output[row, col] = np.sum(kernel *
padded_image[row:row + kernel_row, col:col + kernel_col])
```

Now simply implement the convolution operation using two loops.

```
if average:
    output[row, col] /= kernel.shape[0] * kernel.shape[1]
```

In order to apply the smooth/blur effect we will divide the output pixel by the total number of pixel available in the kernel/filter. This will be done only if the value of average is set `True`.

We are finally done with our simple convolution function. Here is the output image.

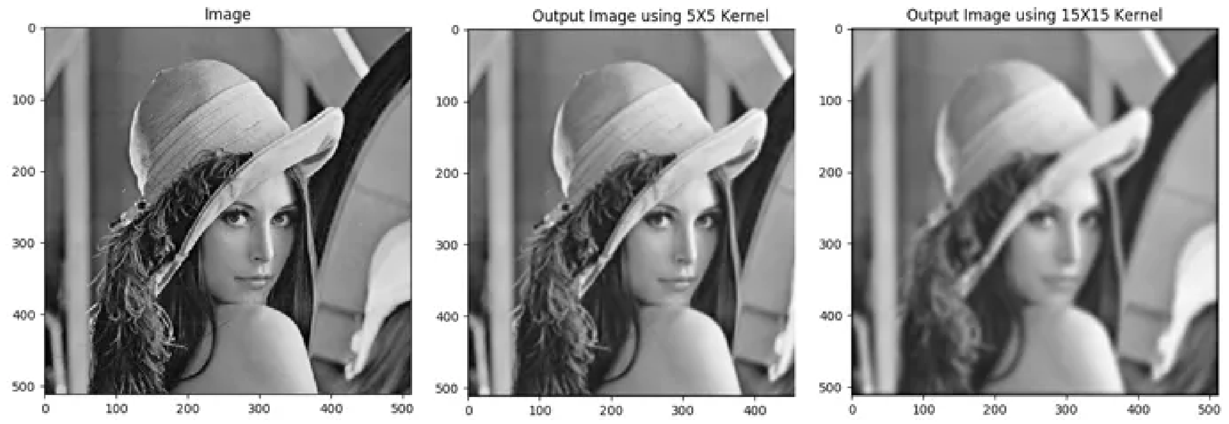


Image
Output Image using 5X5 Kernel
Output Image using 15X15 Kernel

gaussian_blur():

So the `gaussian_blur()` function will call the `gaussian_kernel()` function first to create the kernel and then invoke `convolution()` function.

```
def gaussian_blur(image, kernel_size, verbose=False):
    kernel = gaussian_kernel(kernel_size,
sigma=math.sqrt(kernel_size), verbose=verbose)
    return convolution(image, kernel, average=True,
verbose=verbose)
```

main():

In the main function, we just need to call our `gaussian_blur()` function by passing the arguments.

```
if __name__ == '__main__':
    ap = argparse.ArgumentParser()
    ap.add_argument("-i", "--image", required=True,
help="Path to the image")
    args = vars(ap.parse_args())

    image = cv2.imread(args["image"])

    gaussian_blur(image, 9, verbose=True)
```

Conclusion:

As you have noticed, once we use a larger filter/kernel there is a black border appearing in the final output. This is because we have used zero padding and the color of zero is black. You can implement two different strategies in order to avoid this.

- Don't use any padding, the dimension of the output image will be different but there won't be any dark border.
- Instead of using zero padding, use the edge pixel from the image and use them for padding.

Full Code:

```
import numpy as np
import cv2
import matplotlib.pyplot as plt


def convolution(image, kernel, average=False,
verbose=False):
    if len(image.shape) == 3:
        print("Found 3 Channels :
{}".format(image.shape))
        image = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
        print("Converted to Gray Channel. Size :
{}".format(image.shape))
    else:
        print("Image Shape : {}".format(image.shape))

    print("Kernel Shape : {}".format(kernel.shape))

    if verbose:
        plt.imshow(image, cmap='gray')
        plt.title("Image")
        plt.show()

    image_row, image_col = image.shape
    kernel_row, kernel_col = kernel.shape

    output = np.zeros(image.shape)

    pad_height = int((kernel_row - 1) / 2)
    pad_width = int((kernel_col - 1) / 2)

    padded_image = np.zeros((image_row + (2 * 
pad_height), image_col + (2 * pad_width)))

    padded_image[pad_height:padded_image.shape[0] - 
pad_height, pad_width:padded_image.shape[1] - pad_width] 
= image

    if verbose:
        plt.imshow(padded_image, cmap='gray')
        plt.title("Padded Image")
        plt.show()

    for row in range(image_row):
        for col in range(image_col):
            output[row, col] = np.sum(kernel * 
padded_image[row:row + kernel_row, col:col + kernel_col])
            if average:
                output[row, col] /= kernel.shape[0] * 
kernel.shape[1]

    print("Output Image size : {}".format(output.shape))
    if verbose:
        plt.imshow(output, cmap='gray')
        plt.title("Output Image using {}X{}
Kernel".format(kernel_row, kernel_col))
        plt.show()

    return output
```

```
import numpy as np
import cv2
import argparse
import matplotlib.pyplot as plt
import math
from Computer_Vision.Gaussian_Smoothing.convolution
import convolution


def dnorm(x, mu, sd):
    return 1 / (np.sqrt(2 * np.pi) * sd) * np.e ** (-
np.power((x - mu) / sd, 2) / 2)


def gaussian_kernel(size, sigma=1, verbose=False):
    kernel_1D = np.linspace(-(size // 2), size // 2,
size)
    for i in range(size):
        kernel_1D[i] = dnorm(kernel_1D[i], 0, sigma)
    kernel_2D = np.outer(kernel_1D.T, kernel_1D.T)

    kernel_2D *= 1.0 / kernel_2D.max()

    if verbose:
        plt.imshow(kernel_2D, interpolation='none',
cmap='gray')
        plt.title("Kernel ( {}X{} )".format(size, size))
        plt.show()

    return kernel_2D



def gaussian_blur(image, kernel_size, verbose=False):
    kernel = gaussian_kernel(kernel_size,
sigma=math.sqrt(kernel_size), verbose=verbose)
    return convolution(image, kernel, average=True,
verbose=verbose)



if __name__ == '__main__':
    ap = argparse.ArgumentParser()
    ap.add_argument("-i", "--image", required=True,
help="Path to the image")
    args = vars(ap.parse_args())

    image = cv2.imread(args["image"])

    gaussian_blur(image, 5, verbose=True)
```

Project in Github:

Please find the full project here:

GitHub

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Comments

ZiZi says
April 27, 2020 at 3:28 am

(Edit)

Hi. thank you for sharing this amazing article. I want to implement a sinc filter for my image but I have problems with building the kernel. Could you help me in this matter?

Reply

Abhisek Jana says
April 27, 2020 at 12:09 pm

(Edit)

Hi ZiZi,

Thanks for your feedback !!!

I would be glad to help you however it's been a while I have worked on Signal Processing as I am mainly focusing on ML/DL. Let me recap and see how I can help you.

Thanks,
Abhisek Jana

Reply

ZiZi says
May 6, 2020 at 8:40 am

(Edit)

Hi Abhisek
I 'm so grateful for that.Can I have your email address to send you the complete issue?

Reply

Leroy says
April 13, 2021 at 4:43 am

(Edit)

Hi,
Thanks for this implementation, it really well explained and interesting!
I'm trying to run your code, but cant find the package Computer_Vision which you use in line 6 of the "gaussian_smoothning.py" code .

I'm working with PYCHARM and cant find this package on the list that PYCHARM offers. is there another way to install this package?

Thanks!

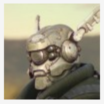
Reply

Abhisek Jana says
April 20, 2021 at 1:24 am

(Edit)

The Computer_Vision is in the same git repository.

Reply



Cluet David says

March 25, 2022 at 10:54 am

(Edit)

Thanks a lot for this really didactic implementation. I was looking for already existing codes to bypass libraries/softwares that become instable nowadays…

Nevertheless, are you sure of this line?:
kernel_2D = np.outer(kernel_1D.T, kernel_1D.T)

as np.outer generates a X * Y 2D array, you just need to transpose one of the 1D kernel. Which works really fine with me.

Now I "just" have to combine your code with map and Pool…

Reply

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Logged in as Abhisek Jana. Edit your profile. Log out? Required fields are marked *

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