Blurring Images

Overview

Teaching: 35 min
Exercises: 25 min

Questions

- How can we apply a low-pass blurring filter to an image?

Objectives

- Explain why applying a low-pass blurring filter to an image is beneficial.
- Apply a Gaussian blur filter to an image using skimage.

In this episode, we will learn how to use skimage functions to blur images.

When processing an image, we are often interested in identifying objects represented within it so that we can perform some further analysis of these ob e.g. by counting them, measuring their sizes, etc. An important concept associated with the identification of objects in an image is that of *edges*: the lines represent a transition from one group of similar pixels in the image to another different group. One example of an edge is the pixels that represent the boundaries of an object in an image, where the background of the image ends and the object begins.

When we blur an image, we make the colour transition from one side of an edge in the image to another smooth rather than sudden. The effect is to aver out rapid changes in pixel intensity. A blur is a very common operation we need to perform before other tasks such as thresholding (../07-thresholding/index.html). There are several different blurring functions in the `skimage.filters` module, so we will focus on just one here, the *Gaussian*

Filters

In the day-to-day, macroscopic world, we have physical filters which separate out objects by size. A filter with small holes allows only small objects throu leaving larger objects behind. This is a good analogy for image filters. A high-pass filter will retain the smaller details in an image, filtering out the large ones. A low-pass filter retains the larger features, analogous to what's left behind by a physical filter mesh. *High-* and *low*-pass, here, refer to high and l *spatial frequencies* in the image. Details associated with high spatial frequencies are small, a lot of these features would fit across an image. Features associated with low spatial frequencies are large - maybe a couple of big features per image.

Blurring

Blurring is to make something less clear or distinct. This could be interpreted quite broadly in the context of image analysis - anything that reduces or distorts the detail of an image might apply. Applying a low pass filter, which removes detail occurring at high spatial frequencies, is perceived as a blurri effect. A Gaussian blur is a filter that makes use of a Gaussian kernel.

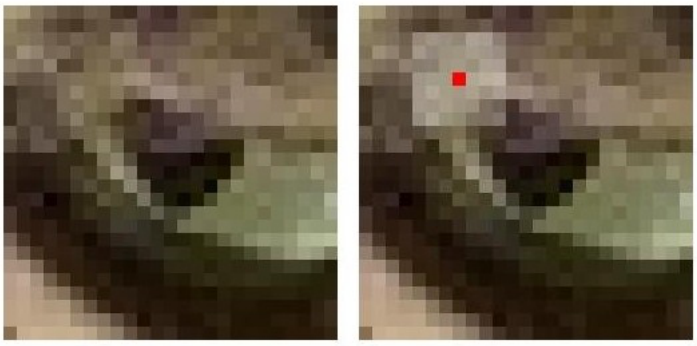
Kernels

A kernel can be used to implement a filter on an image. A kernel, in this context, is a small matrix which is combined with the image using a mathematic technique: *convolution*. Different sizes, shapes and contents of kernel produce different effects. The kernel can be thought of as a little image in itself, will favour features of a similar size and shape in the main image. On convolution with an image, a big, blobby kernel will retain big, blobby, low spatial frequency features.

Gaussian blur

Consider this image of a cat, in particular the area of the image outlined by the white square.

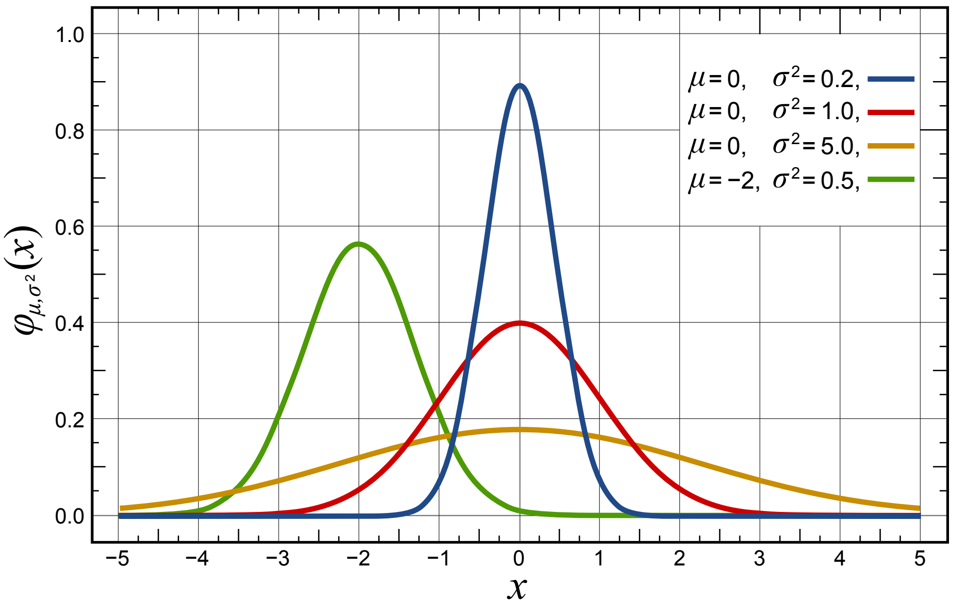
Now, zoom in on the area of the cat’s eye, as shown in the left-hand image below. When we apply a filter, we consider each pixel in the image, one at a tin
this example, the pixel we are currently working on is highlighted in red, as shown in the right-hand image.



When we apply a filter, we consider rectangular groups of pixels surrounding each pixel in the image, in turn. The *kernel* is another group of pixels (a sepa
matrix / small image), of the same dimensions as the rectangular group of pixels in the image, that moves along with the pixel being worked on by the filt
The width and height of the kernel must be an odd number, so that the pixel being worked on is always in its centre. In the example shown above, the ker
is square, with a dimension of seven pixels.

To apply the kernel to the current pixel, an average of the the colour values of the pixels surrounding it is calculated, weighted by the values in the kernel
Gaussian blur, the pixels nearest the centre of the kernel are given more weight than those far away from the centre. The rate at which this weight dimin
is determined by a Gaussian function, hence the name Gaussian blur.

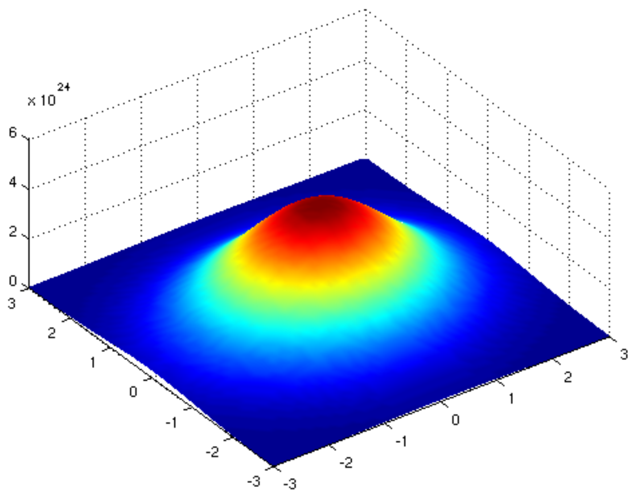
A Gaussian function maps random variables into a normal distribution or “Bell Curve”.



https://en.wikipedia.org/wiki/Gaussian_function#/media/File:Normal_Distribution_PDF.svg

The shape of the function is described by a mean value μ, and a variance value σ². The mean determines the central point of the bell curve on the x axis, a
the variance describes the spread of the curve.

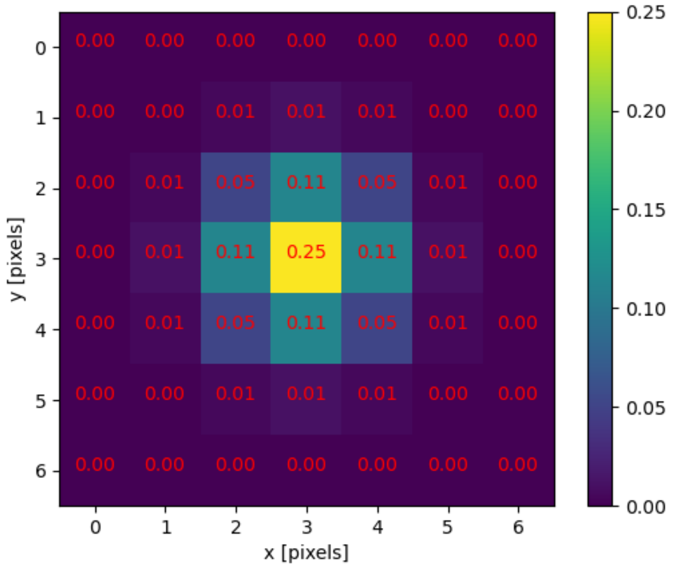
In fact, when using Gaussian functions in Gaussian blurring, we use a 2D Gaussian function to account for X and Y dimensions, but the same rules apply. T
mean μ is always 0, and represents the middle of the 2D kernel. Increasing values of σ² in either dimension increases the amount of blurring in that dimer



https://commons.wikimedia.org/wiki/File:Gaussian_2D.png

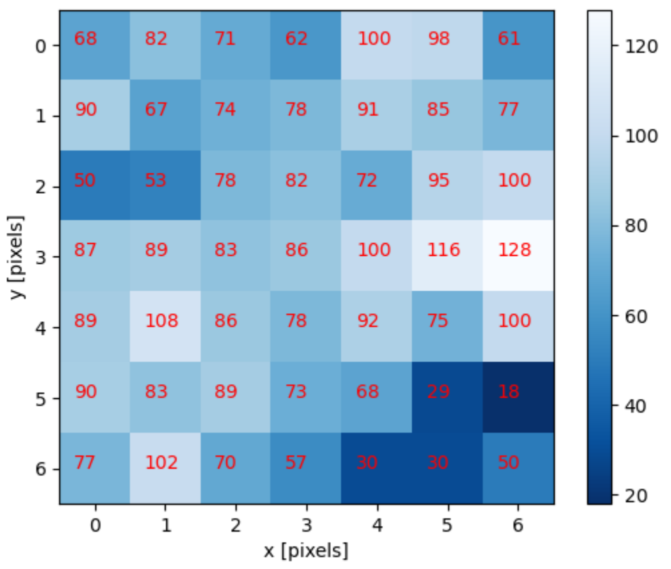
The averaging is done on a channel-by-channel basis, and the average channel values become the new value for the pixel in the filtered image. Larger ker
have more values factored into the average, and this implies that a larger kernel will blur the image more than a smaller kernel.

To get an idea of how this works, consider this plot of the two-dimensional Gaussian function:

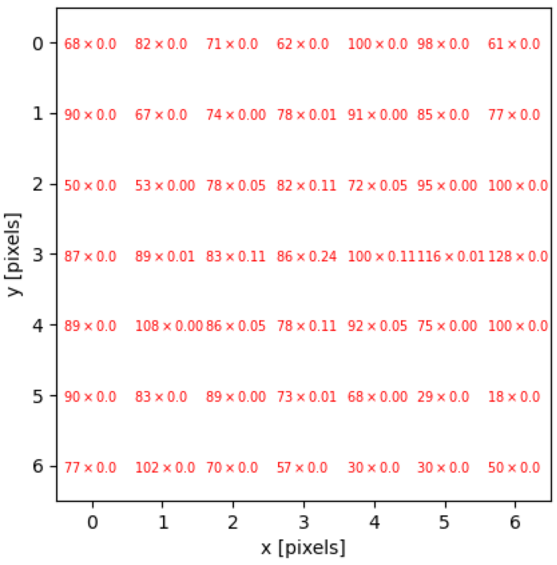


Imagine that plot laid over the kernel for the Gaussian blur filter. The height of the plot corresponds to the weight given to the underlying pixel in the ker
I.e., the pixels close to the centre become more important to the filtered pixel colour than the pixels close to the outer limits of the kernel. The shape of
Gaussian function is controlled via its standard deviation, or sigma. A large sigma value results in a flatter shape, while a smaller sigma value results in a
pronounced peak. The mathematics involved in the Gaussian blur filter are not quite that simple, but this explanation gives you the basic idea.

To illustrate the blur process, consider the blue channel colour values from the seven-by-seven region of the cat image above:



The filter is going to determine the new blue channel value for the centre pixel – the one that currently has the value 86. The filter calculates a weighted average of all the blue channel values in the kernel giving higher weight to the pixels near the centre of the kernel.



y [pixels] \ x [pixels]	0	1	2	3	4	5	6
0	68 × 0.0	82 × 0.0	71 × 0.0	62 × 0.0	100 × 0.0	98 × 0.0	61 × 0.0
1	90 × 0.0	67 × 0.0	74 × 0.00	78 × 0.01	91 × 0.00	85 × 0.0	77 × 0.0
2	50 × 0.0	53 × 0.00	78 × 0.05	82 × 0.11	72 × 0.05	95 × 0.00	100 × 0.0
3	87 × 0.0	89 × 0.01	83 × 0.11	86 × 0.24	100 × 0.11	116 × 0.01	128 × 0.0
4	89 × 0.0	108 × 0.00	86 × 0.05	78 × 0.11	92 × 0.05	75 × 0.00	100 × 0.0
5	90 × 0.0	83 × 0.0	89 × 0.00	73 × 0.01	68 × 0.00	29 × 0.0	18 × 0.0
6	77 × 0.0	102 × 0.0	70 × 0.0	57 × 0.0	30 × 0.0	30 × 0.0	50 × 0.0

This weighted average, the sum of the multiplications, becomes the new value for the centre pixel (3, 3). The same process would be used to determine t
green and red channel values, and then the kernel would be moved over to apply the filter to the next pixel in the image.

📌 Image edges

Something different needs to happen for pixels near the outer limits of the image, since the kernel for the filter may be partially off the image. For example, what happens when the filter is applied to the upper-left pixel of the image? Here are the blue channel pixel values for the upper-left pixel of cat image, again assuming a seven-by-seven kernel:

Output

```
x  x  x  x  x  x  x
x  x  x  x  x  x  x
x  x  x  x  x  x  x
x  x  x  4  5  9  2
x  x  x  5  3  6  7
x  x  x  6  5  7  8
x  x  x  5  4  5  3
```

The upper-left pixel is the one with value 4. Since the pixel is at the upper-left corner, there are no pixels underneath much of the kernel; here, this is represented by x's. So, what does the filter do in that situation?

The default mode is to fill in the *nearest* pixel value from the image. For each of the missing x's the image value closest to the x is used. If we fill in a fev the missing pixels, you will see how this works:

Output

```
x  x  x  4  x  x  x
x  x  x  4  x  x  x
x  x  x  4  x  x  x
4  4  4  4  5  9  2
x  x  x  5  3  6  7
x  x  x  6  5  7  8
x  x  x  5  4  5  3
```

Another strategy to fill those missing values is to *reflect* the pixels that are in the image to fill in for the pixels that are missing from the kernel.

Output

```
x  x  x  5  x  x  x
x  x  x  6  x  x  x
x  x  x  5  x  x  x
2  9  5  4  5  9  2
x  x  x  5  3  6  7
x  x  x  6  5  7  8
x  x  x  5  4  5  3
```

A similar process would be used to fill in all of the other missing pixels from the kernel. Other *border modes* are available; you can learn more about the in the skimage documentation (https://scikit-image.org/docs/dev/user_guide).

This animation shows how the blur kernel moves along in the original image in order to calculate the colour channel values for the blurred image.

skimage has built-in functions to perform blurring for us, so we do not have to perform all of these mathematical operations ourselves. Let's work throug example of blurring an image with the skimage Gaussian blur function.

First, import the packages needed for this episode

Python

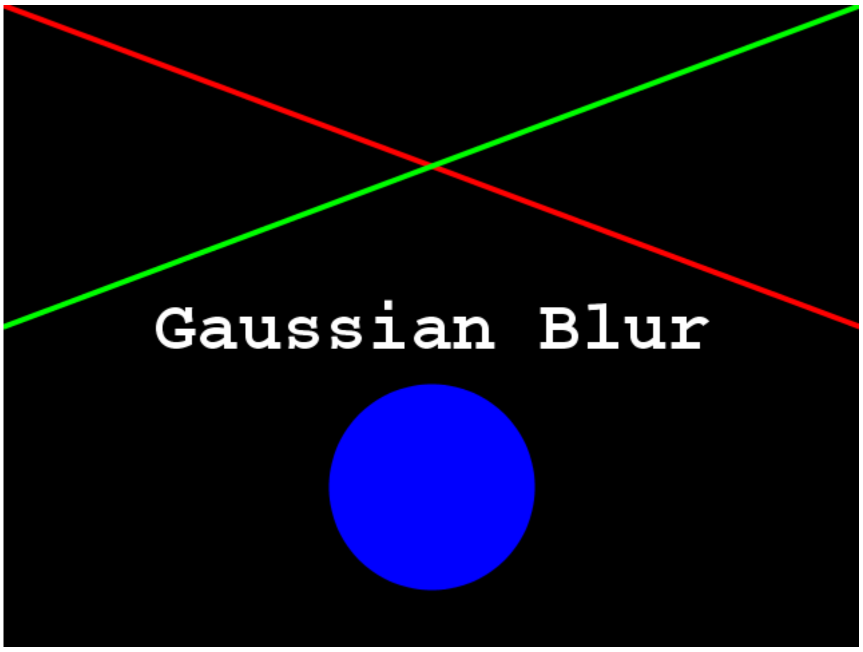
```
import matplotlib.pyplot as plt
import ipympl
import imageio.v3 as iio
import skimage
import skimage.filters
%matplotlib widget
```

Then, we load the image, and display it:

Python

```
image = iio.imread(uri="data/gaussian-original.png")

# display the image
fig, ax = plt.subplots()
plt.imshow(image)
```



Next, we apply the gaussian blur:

Python

```
sigma = 3.0

# apply Gaussian blur, creating a new image
blurred = skimage.filters.gaussian(
    image, sigma=(sigma, sigma), truncate=3.5, channel_axis=2)
```

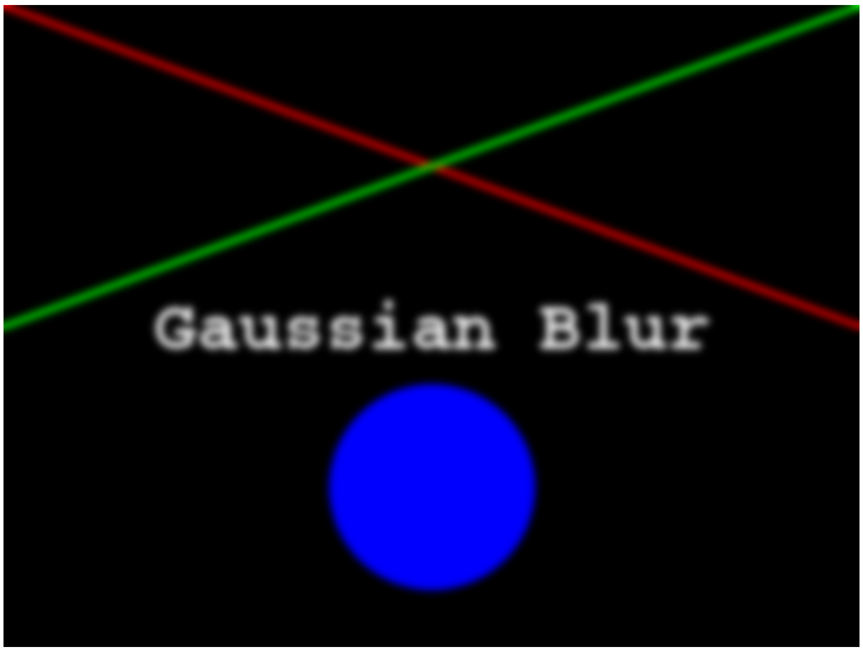
The first two parameters to `skimage.filters.gaussian()` are the image to blur, `image`, and a tuple defining the sigma to use in ry- and cx-direction, `(sigma, sigma)`. The third parameter `truncate` gives the radius of the kernel in terms of sigmas. A Gaussian function is defined from -infinity to +infin but our kernel (which must have a finite, smaller size) can only approximate the real function. Therefore, we must choose a certain distance from the cen of the function where we stop this approximation, and set the final size of our kernel. In the above example, we set `truncate` to 3.5, which means the ke size will be 2 * sigma * 3.5. For example, for a `sigma` of 1.0 the resulting kernel size would be 7, while for a `sigma` of 2.0 the kernel size would be 14. The default value for `truncate` in scikit-image is 4.0.

The last parameter to `skimage.filters.gaussian()` tells skimage to interpret our image, that has three dimensions, as a multichannel colour image.

Finally, we display the blurred image:

Python

```
# display blurred image
fig, ax = plt.subplots()
plt.imshow(blurred)
```



Experimenting with sigma values (10 min)

The size and shape of the kernel used to blur an image can have a significant effect on the result of the blurring and any downstream analysis carried ou on the blurred image. The next two exercises ask you to experiment with the sigma values of the kernel, which is a good way to develop your understanding of how the choice of kernel can influence the result of blurring.

First, try running the code above with a range of smaller and larger sigma values. Generally speaking, what effect does the sigma value have on the blur image?

Solution

Generally speaking, the larger the sigma value, the more blurry the result. A larger sigma will tend to get rid of more noise in the image, which will help for other operations we will cover soon, such as thresholding. However, a larger sigma also tends to eliminate some of the detail from the image. So, we must strike a balance with the sigma value used for blur filters.

Experimenting with kernel shape (10 min - optional, not included in timing)

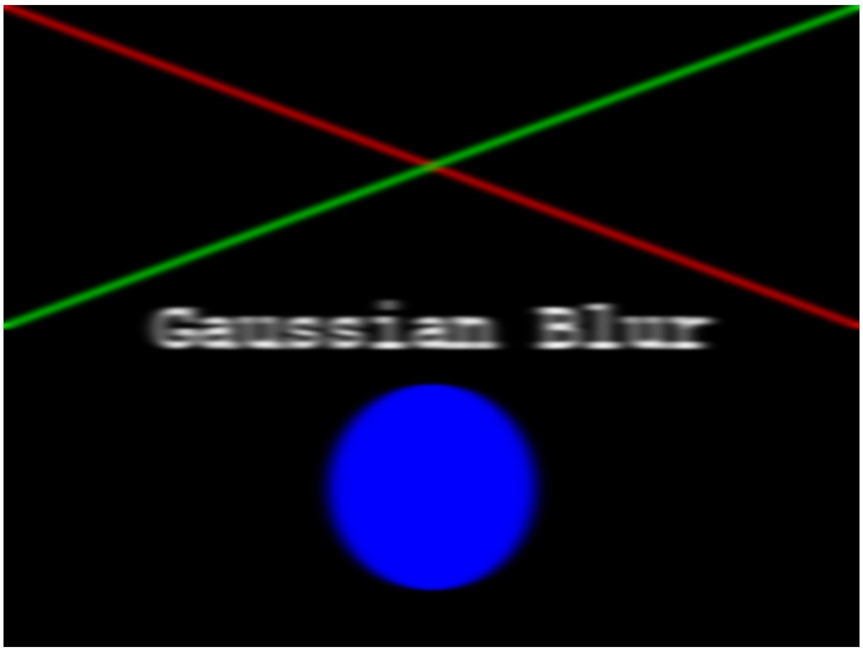
Now, what is the effect of applying an asymmetric kernel to blurring an image? Try running the code above with different sigmas in the ry and cx directi For example, a sigma of 1.0 in the ry direction, and 6.0 in the cx direction.

Solution

Python

```
# apply Gaussian blur, with a sigma of 1.0 in the ry direction, and 6.0 in the cx direction
blurred = skimage.filters.gaussian(
    image, sigma=(1.0, 6.0), truncate=3.5, channel_axis=-1
)

# display blurred image
fig, ax = plt.subplots()
plt.imshow(blurred)
```



These unequal sigma values produce a kernel that is rectangular instead of square. The result is an image that is much more blurred in the x direction than the y direction. For most use cases, a uniform blurring effect is desirable and this kind of asymmetric blurring should be avoided. However, it can b helpful in specific circumstances e.g. when noise is present in your image in a particular pattern or orientation, such as vertical lines, or when you want t remove uniform noise without blurring edges present in the image in a particular orientation (https://www.researchgate.net/publication/228567435_An_edge_detection_algorithm_based_on_rectangular_Gaussian_kernels_for_machine_vision_a

Other methods of blurring

The Gaussian blur is a way to apply a low-pass filter in skimage. It is often used to remove Gaussian (i. e., random) noise from the image. For other kinds o noise, e.g. "salt and pepper", a median filter is typically used. See the `skimage.filters` documentation (https://scikit-image.org/docs/dev/api/skimage.filters.html#module-skimage.filters) for a list of available filters.

Key Points

- Applying a low-pass blurring filter smooths edges and removes noise from an image.
- Blurring is often used as a first step before we perform thresholding or edge detection.
- The Gaussian blur can be applied to an image with the `skimage.filters.gaussian()` function.
- Larger sigma values may remove more noise, but they will also remove detail from an image.

(/image-processing/05-creating-histograms/index.html)

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