810 lines (810 sloc) | 720 KB

Raw Blame

Image Enhancement - Image Histogram

Import required packages necessary for image processing.

In [1]:

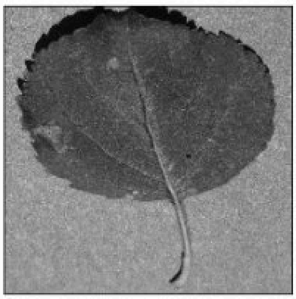
```
import cv2
import matplotlib.pyplot as plt
import numpy as np
%matplotlib inline
```

In [3]:

```
img = cv2.imread('/content/00e909aa-e3ae-4558-9961-336bb0f35db3___JR_FrgE.S 8593.JPG', 0)
plt.imshow(img, cmap='gray'), plt.grid(False)
plt.xticks([]), plt.yticks([])
```

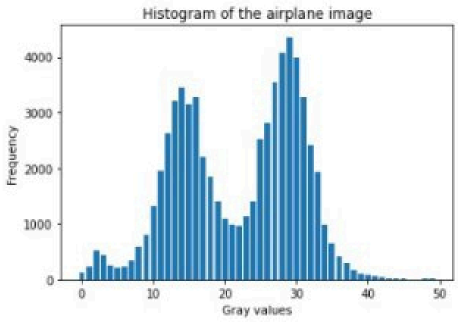
Out[3]:

```
(([], ),
 ([], ))
```

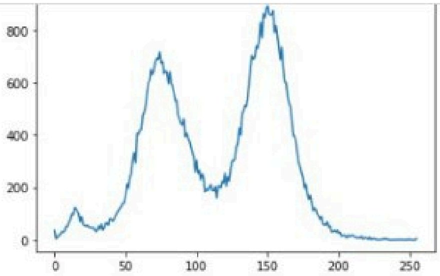


In [5]:
```
hist = cv2.calcHist([img],[0],None,[50],[0,256])

# different methods for displaying a histogram
plt.bar(range(50), hist.ravel())
plt.title('Histogram of the airplane image')
plt.xlabel('Gray values')
plt.ylabel('Frequency')
```

Out[5]: Text(0, 0.5, 'Frequency')



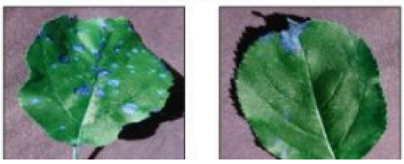
In [6]:
```
# Another method
hist,bins = np.histogram(img.ravel(),256,[0,256])
plt.plot(hist)
```



Let's look at another example.

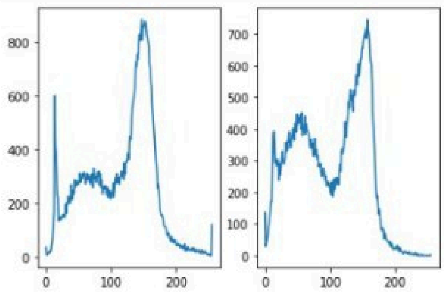
In [7]:
```
# Let's read two other images
high = cv2.imread('/content/0bc40cc3-6a85-480e-a22f-967a866a56a1___JR_FrgE.S 2784.JPG')
low = cv2.imread('/content/0c8432e0-0484-470c-a774-7cce596b9e64___JR_FrgE.S 2841.JPG')
```

In [10]:
```
# show images
plt.subplot(121), plt.imshow(high)
plt.grid(False), plt.xticks([]), plt.yticks([])

plt.subplot(122), plt.imshow(low)
plt.grid(False), plt.xticks([]), plt.yticks([])
plt.show()
```



In [11]:

```
# Calculate histogram of both images for the last channel.
# Channels can differ from 0 to 2.
hist_high = cv2.calcHist([high],[2],None,[256],[0,256])
hist_low = cv2.calcHist([low],[2],None,[256],[0,256])

# Plot histograms
plt.subplot(121)
plt.plot(hist_high)

plt.subplot(122)
plt.plot(hist_low)

plt.show()
```



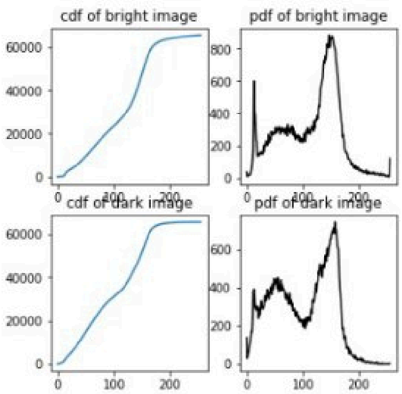
2-Cumulative histogram of an image

Calculate cumulative distribution function (CDF) of an image

The cumulative histogram of an image is produced by calculating the cumulative sum of that image's histogram. There is no specific function in OpenCV to obtain the CDF of an image; thus we use the cumsum function in Numpy. You can find more about the function here

In [12]:

```
cdf_low = hist_low.cumsum()
cdf_high = hist_high.cumsum()

# plot cumulative histograms
plt.subplot(221), plt.plot(cdf_high), plt. title('cdf of bright image')
plt.subplot(222), plt.plot(hist_high, 'k'), plt. title('pdf of bright image')

plt.subplot(223), plt.plot(cdf_low), plt. title('cdf of dark image')
plt.subplot(224), plt.plot(hist_low, 'k'), plt. title('pdf of dark image')

# adjust the placement of subplots
plt.subplots_adjust(bottom=2, right=0.8, top=3)

plt.show()
```

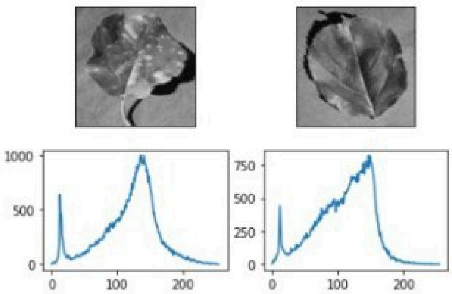


3-Histogram manipulation

In order to continue image manipulation, first of all, we change the RGB images to grayscale using `cv2.cvtColor()`.

In [13]:
```
low_gray = cv2.cvtColor(low, cv2.COLOR_BGR2GRAY)
high_gray = cv2.cvtColor(high, cv2.COLOR_BGR2GRAY)
```

In [14]:
```
# show images and their histograms
plt.subplot(221), plt.imshow(high_gray, cmap='gray')
plt.grid(False), plt.xticks([]), plt.yticks([])
plt.subplot(223), plt.plot(cv2.calcHist([high_gray],[0],None,[256],[0,256]))

plt.subplot(222), plt.imshow(low_gray, cmap='gray')
plt.grid(False), plt.xticks([]), plt.yticks([])
plt.subplot(224), plt.plot(cv2.calcHist([low_gray],[0],None,[256],[0,256]))

plt.show()
```



3-1 Brightness

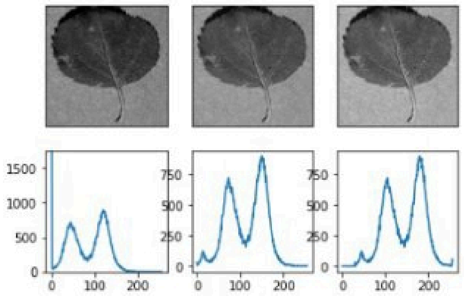
In [15]:

```python
# Define a function to easily handle manipulation.
def manip_image(image, alpha, beta):

  new_image = np.zeros(image.shape, image.dtype)

  for y in range(image.shape[0]):
    for x in range(image.shape[1]):
        new_image[y,x] = np.clip(alpha*image[y,x] + beta, 0, 255)

  return new_image
```

In [16]:

```python
# Test on the image
bright = manip_image(img, 1, 30)
dark = manip_image(img, 1, -30)

# Compare the results
plt.figure()
plt.subplot(231), plt.imshow(dark, cmap='gray')
plt.grid(False), plt.xticks([]), plt.yticks([])

plt.subplot(232), plt.imshow(img, cmap='gray')
plt.grid(False), plt.xticks([]), plt.yticks([])


plt.subplot(233),plt.imshow(bright, cmap='gray')
plt.grid(False), plt.xticks([]), plt.yticks([])

plt.subplot(234)
plt.plot(cv2.calcHist([dark],[0],None,[256],[0,256])), plt.ylim((0, 1750))

plt.subplot(235)
plt.plot(cv2.calcHist([img],[0],None,[256],[0,256]))

plt.subplot(236)
plt.plot(cv2.calcHist([bright],[0],None,[256],[0,256]))
```

Out[16]: []



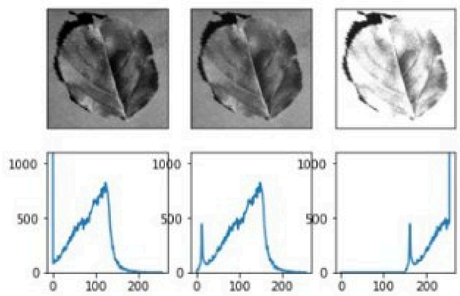
You can see the histogram forward and backward shifts. When we increase and decrease brightness, histogram moves to brighter and darker regions, respectively.

In [17]:

```
# Test on the dark image
l_bright = manip_image(low_gray, 1, 150)
l_dark = manip_image(low_gray, 1, -25)

# Compare the results
plt.figure()
plt.subplot(231), plt.imshow(l_dark, cmap='gray')
plt.grid(False), plt.xticks([]), plt.yticks([])

plt.subplot(232), plt.imshow(low_gray, cmap='gray')
plt.grid(False), plt.xticks([]), plt.yticks([])


plt.subplot(233),plt.imshow(l_bright, cmap='gray')
plt.grid(False), plt.xticks([]), plt.yticks([])

plt.subplot(234)
plt.plot(cv2.calcHist([l_dark],[0],None,[256],[0,256])), plt.ylim((0, 1100))
```

```
plt.subplot(233),plt.imshow(l_bright, cmap='gray')
plt.grid(False), plt.xticks([]), plt.yticks([])

plt.subplot(234)
plt.plot(cv2.calcHist([l_dark],[0],None,[256],[0,256])), plt.ylim((0, 1100))

plt.subplot(235)
plt.plot(cv2.calcHist([low_gray],[0],None,[256],[0,256])), plt.ylim((0, 1100))

plt.subplot(236)
plt.plot(cv2.calcHist([l_bright],[0],None,[256],[0,256])), plt.ylim((0, 1100))
```

Out[17]: ([], (0.0, 1100.0))



3-2 Contrast

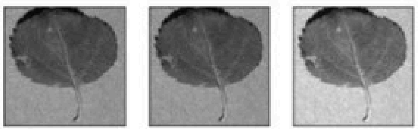
Contrast of an image could be defined in different ways. One simple rule of thumb is to behave contrast as the distance between largest and smallest values in an image. In fact, the more the gray values are distributed over the $2^k - 1$ range, the more the contrast will be.

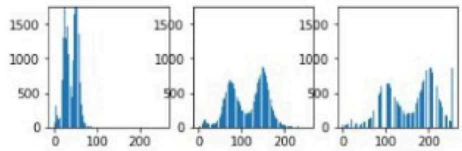
A uniform histogram with values distributed uniformly all over the intensity range will have the highest contrast. This will be the concept of our next section, Histogram

In [18]:

```python
# Test on the image
increase_contrast = manip_image(img, 1.35, 0)
decrease_contrast = manip_image(img, 0.35, 0)

# Compare the results
plt.figure()
plt.subplot(231), plt.imshow(decrease_contrast, cmap='gray')
plt.grid(False), plt.xticks([]), plt.yticks([])

plt.subplot(232), plt.imshow(img, cmap='gray')
plt.grid(False), plt.xticks([]), plt.yticks([])


plt.subplot(233),plt.imshow(increase_contrast, cmap='gray')
plt.grid(False), plt.xticks([]), plt.yticks([])

plt.subplot(234)
plt.bar(range(256),
        cv2.calcHist([decrease_contrast],[0],None,[256],[0,256]).ravel())
plt.ylim((0, 1750))

plt.subplot(235)
plt.bar(range(256),
        cv2.calcHist([img],[0],None,[256],[0,256]).ravel())
plt.ylim((0, 1750))

plt.subplot(236)
plt.bar(range(256),
        cv2.calcHist([increase_contrast],[0],None,[256],[0,256]).ravel())
plt.ylim((0, 1750))
```

Out[18]: (0.0, 1750.0)





Histogram equalization

One usual method to stretch the intensity values of an image in order to make its histogram similar to the perfect histogram shape (uniformly distributed), is the *histogram equalization*. In this method, image histogram will be stretched with respect to its cumulative distribution function. Very good explanation of histogram equalization is found in here.

cv2.equalizeHist(src[, dst])

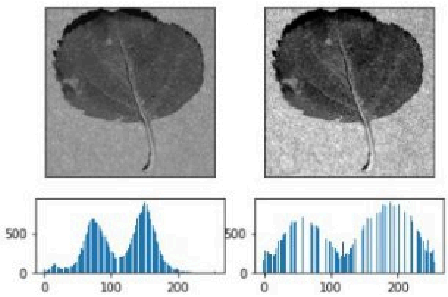
src : the only required argument is the original image to be equalized.

In [19]:

```
img_eq = cv2.equalizeHist(img)

grid = plt.GridSpec(3, 4, wspace=0.4, hspace=0.3)

plt.subplot(grid[:2, :2])
plt.imshow(img, cmap='gray')
plt.grid(False), plt.xticks([]), plt.yticks([])

plt.subplot(grid[:2, 2:])
plt.imshow(img_eq, cmap='gray')
plt.grid(False), plt.xticks([]), plt.yticks([])

plt.subplot(grid[2, :2])
plt.bar(range(256),
        cv2.calcHist([img],[0],None,[256],[0,256]).ravel())
```

```python
plt.subplot(grid[:2, 2:])
plt.imshow(img_eq, cmap='gray')
plt.grid(False), plt.xticks([]), plt.yticks([])

plt.subplot(grid[2, :2])
plt.bar(range(256),
        cv2.calcHist([img],[0],None,[256],[0,256]).ravel())

plt.subplot(grid[2, 2:])
plt.bar(range(256),
        cv2.calcHist([img_eq],[0],None,[256],[0,256]).ravel())
```

Out[19]:



CLAHE (Contrast Limited Adaptive Histogram Equalization)

As you can see above, some parts of the image are brighter than the other parts in the equalized image. In order to reduce these artifacts in image enhancement, an adaptive algorithm was developed. This algorithm performs the same histogram equalization, but in small tiles of the image; resulting in better visual feelings.

To perform CLAHE, a CLAHE object should be created first. Then it is applied over the image. Two parameters, the *tile number* and *limit* should be specified.

You can try different tile sizes and limits and check the enhancement of image.

In [20]:

```python
clahe = cv2.createCLAHE(clipLimit=2.0, tileGridSize=(16, 16))
img_cl = clahe.apply(img)

grid = plt.GridSpec(3, 4, wspace=0.4, hspace=0.3)

plt.subplot(grid[:2, :2])
plt.imshow(img, cmap='gray')
plt.grid(False), plt.xticks([]), plt.yticks([])

plt.subplot(grid[:2, 2:])
plt.imshow(img_cl, cmap='gray')
plt.grid(False), plt.xticks([]), plt.yticks([])

plt.subplot(grid[2, :2])
plt.bar(range(256),
        cv2.calcHist([img],[0],None,[256],[0,256]).ravel())

plt.subplot(grid[2, 2:])
plt.bar(range(256),
        cv2.calcHist([img_cl],[0],None,[256],[0,256]).ravel())
```

Out[20]: