Lowpass Gaussian Filter Kernels

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1 Lowpass Gaussian Filter Kernels

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[1]:
```
%matplotlib inline
```

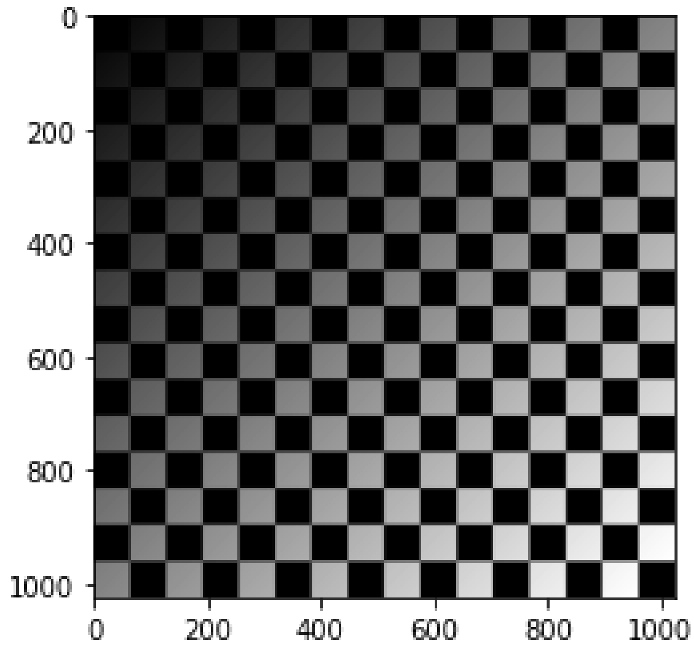
[2]:
```
from IPython.display import display, Math, Latex
import numpy as np
import matplotlib.pyplot as plt
from PIL import Image

from scipy import signal
from scipy import misc
```

1.1 Original Image (Chessboard)

- use scipy.signal and numpy in this part

[3]:
```
img = Image.open('checkerboard1024-shaded.tif')
plt.imshow(img, cmap=plt.get_cmap('gray'))
np.asarray(img).shape
```

[3]: (1024, 1024)

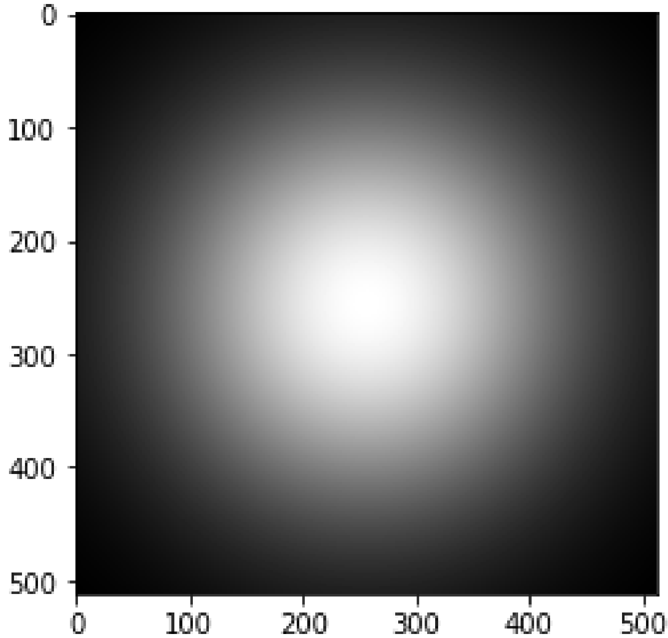


1.2 Shading Correction with Gaussian Kernel

1.2.1 Make a Gaussian Kernel with $\sigma = 128, 512 \times 512$

[4]:
```
n1= 512
sigma1 = 128
x, y = np.mgrid[-n1/2:n1/2, -n1/2:n1/2]
kernel1 = np.exp(-(x**2+y**2)/(2*(sigma1**2)))
plt.imshow(kernel1, cmap=plt.get_cmap('gray'))
```

[4]:
```
<matplotlib.image.AxesImage at 0x1e8a1e7a640>
```



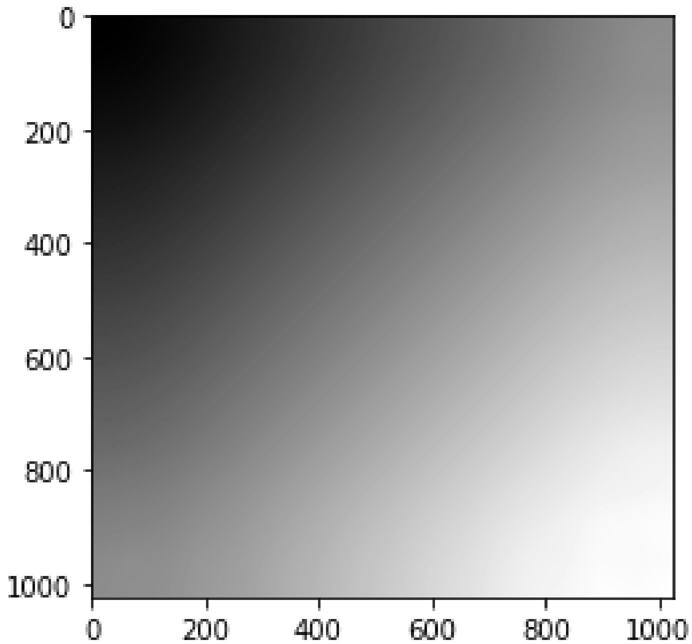
1.2.2 Compute the Convolution Directly

- shade $\approx$ filter $\star$ img
- this would take a long time $O(n^2 \times N^2)$

[5]:
```
shade = signal.convolve2d(img, kernel1, boundary='symm', mode='same')
```

[6]:
```
plt.imshow(shade, cmap=plt.get_cmap('gray'))
```

[6]:
```
<matplotlib.image.AxesImage at 0x1e8a1ecfd00>
```



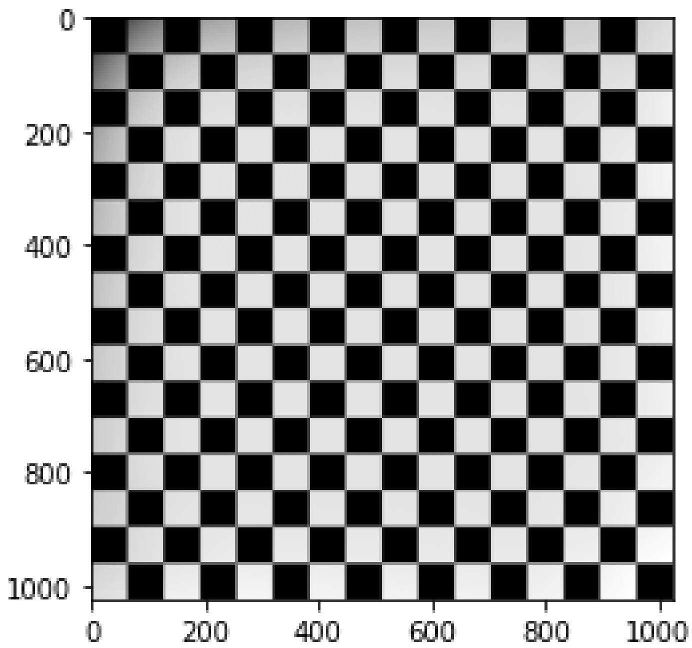
1.2.3 Correct the shading

- $\text{img}_{\text{corrected}} = \text{img}/\text{shade}$

[7]:
```
img_corrected = img/shade
```

[8]:
```
plt.imshow(img_corrected, cmap=plt.get_cmap('gray'))
```

[8]: <matplotlib.image.AxesImage at 0x1e8a30a05e0>



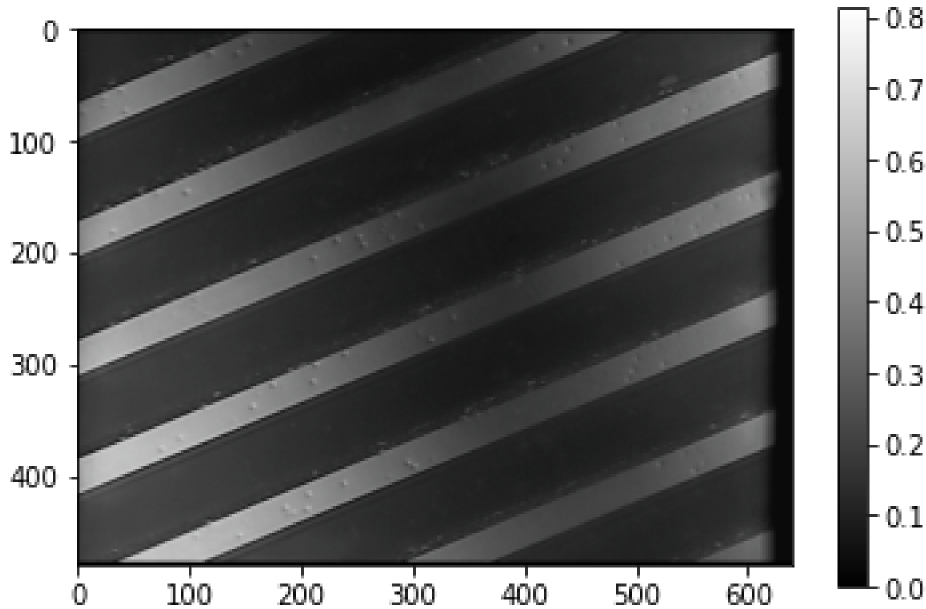
1.3 Original Image (N1.bmp)

- use opencv in this part

[9]:
```
import cv2
```

[10]:
```
img2 = cv2.imread("N1.bmp")
img2 = img2/255 # normalize to [0,1]
plt.imshow(img2, cmap=plt.get_cmap('gray'))
plt.colorbar()
np.asarray(img2).shape
```

[10]: (480, 640, 3)



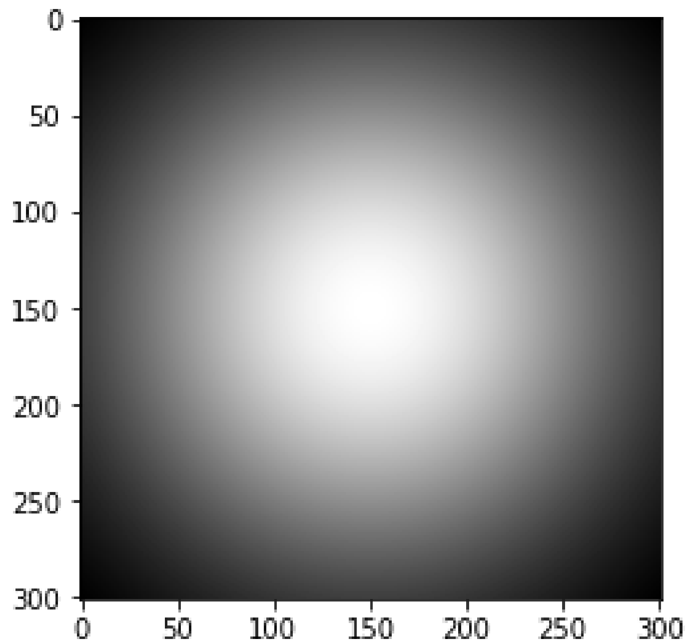
1.4 Shading Correction with Gaussian Kernel

1.4.1 Use cv2 for Gaussian Blurring

- $\sigma \approx$ the width of the pattern
- choose appropriate $n (\approx \sigma * 3)$
- $\text{shade}_2 = \text{GaussianFilter}(n, n, \sigma) \star \text{img}_2$

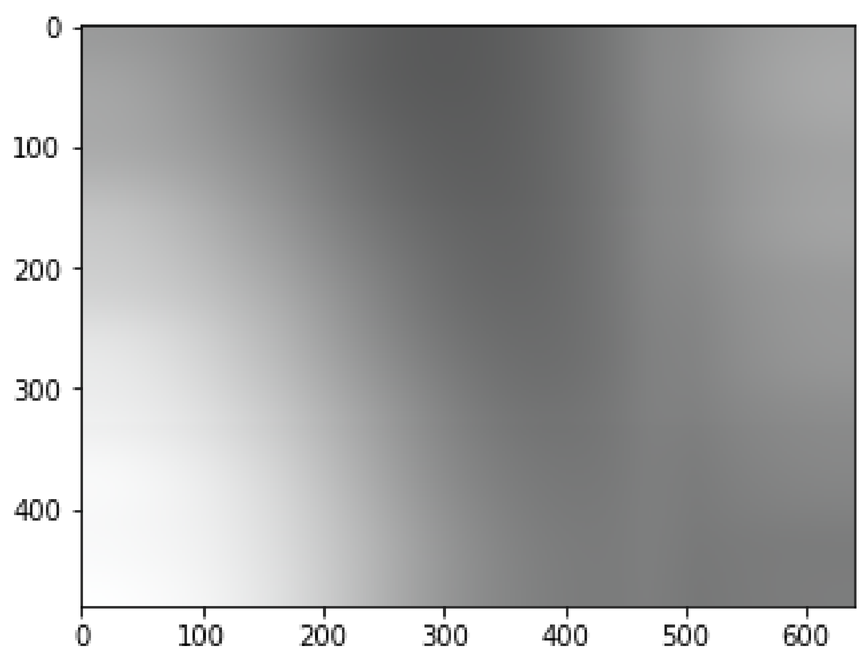
[11]:
```
sigma2 = 100 # about the width of the pattern
n2 = 301 # must be odd
kernel2 = cv2.getGaussianKernel(n2, sigma2)
kernel2 = np.outer(kernel2, kernel2)
plt.imshow(kernel2, cmap='gray')
```

[11]:
```
<matplotlib.image.AxesImage at 0x1e8a1e1fee0>
```



[12]:
```
shade2 = cv2.GaussianBlur(img2, (n2, n2), sigma2)
shade2 = cv2.normalize(shade2, shade2, 1.0, 0.0, cv2.NORM_INF, dtype=cv2.
↪CV_32F) # normalize to [0,1]
plt.imshow(shade2, cmap='gray')
```

[12]: <matplotlib.image.AxesImage at 0x1e8a1f56370>

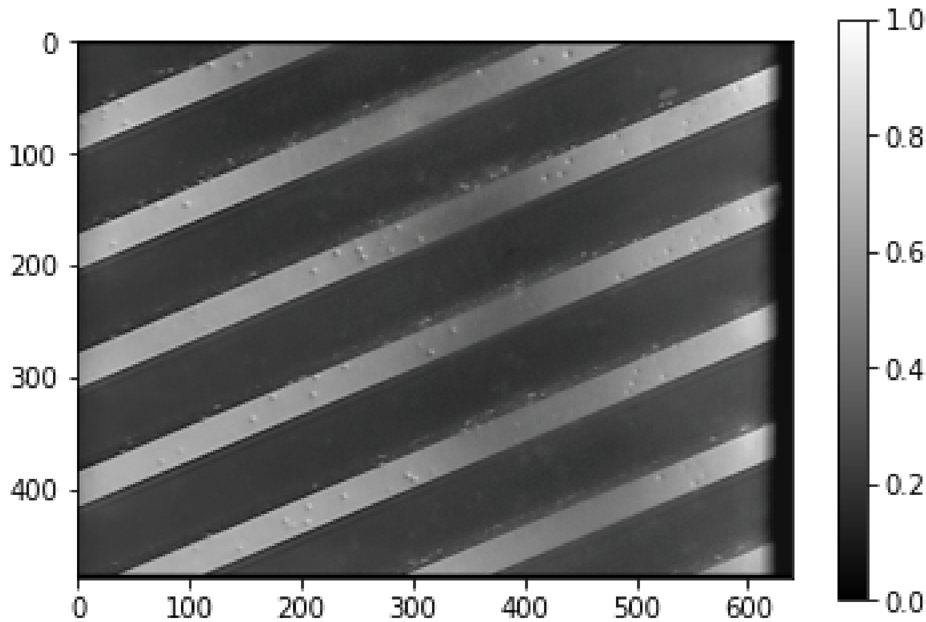


1.4.2 Correct the shading

- $\text{img}_{\text{corrected}} = \text{img}/\text{shade}$

[13]:
```
img_corrected_2 = img2/shade2
img_corrected_2 = cv2.normalize(img_corrected_2, img_corrected_2, 1.0, 0.0, cv2.
↪NORM_INF, dtype=cv2.CV_32F) # normalize to [0,1]
plt.imshow(img_corrected_2, cmap='gray')
plt.colorbar()
```

[13]:
```
<matplotlib.colorbar.Colorbar at 0x1e8a1fd7d30>
```



1.5 Remarks

For image shading correction, the σ is chosen to be around the width of the pattern and the kernel size is taken so that the pattern does not appears in the resulting (estimated) shaded pattern noise.

- the first kernel
  - pattern size $\approx \frac{1024}{16} \times 2$
  - $n = 512, \sigma = 128$
- the second kernel
  - pattern size ≈ 100
  - $n = 301, \sigma = 100$
- The larger σ is, the kernel adapts more information from farther pixels, or equivalently, information from each pixel spreads farther.

- The parameter n means the range that we consider the Gaussian Filter effective (since it drops exponentially fast).

[15]:
```
fig, axs = plt.subplots(2, 4)
fig.suptitle("Comparisons", fontsize=15)

collections = [0,0]
collections[0] = [img, kernel1, shade, img_corrected]
collections[1] = [img2, kernel2, shade2, img_corrected_2]
# title
axs[0][0].set_title("original", fontsize=10)
axs[0][1].set_title("kernel", fontsize=10)
axs[0][2].set_title("shadig noise", fontsize=10)
axs[0][3].set_title("corrected", fontsize=10)
## arrangement
for i in range(2):
    for j in range(4):
        axs[i][j].imshow(collections[i][j], cmap='gray')
        axs[i][j].axis('off')
```