Test of Python analysis

https://scikit-image.org/docs/dev/auto_examples/filters/plot_nonlocal_means.html (https://scikit-image.org/docs/dev/auto_examples/filters/plot_nonlocal_means.html)

Works well for random gaussian noise but not as good for salt and pepper https://www.iro.umontreal.ca/~mignotte/IFT6150/Articles/Buades-NonLocal.pdf (https://www.iro.umontreal.ca/~mignotte/IFT6150/Articles/Buades-NonLocal.pdf)

The non-local means algorithm replaces the value of a pixel by an average of a selection of other pixels values: small patches centered on the other pixels are compared to the patch centered on the pixel of interest, and the average is performed only for pixels that have patches close to the current patch.

In [1]:
```
import cv2
import numpy as np
from skimage import io, img_as_float
from skimage.restoration import denoise_nl_means, estimate_sigma
from matplotlib import pyplot as plt
from tifffile import imread
```

1) Read an image in FLOAT with io.imread or with tifffile.imread

io.imread

In [2]:
```
#import our images as float (this is the format that skimage likes)
img_blue = img_as_float(io.imread('247010 vim-g lamp2-r 20x010/nd_cropc1.tif', as_gray=True))
#img_green = img_as_float(io.imread('247010 vim-g lamp2-r 20x010/nd_cropc2.tif', as_gray=True))
#img_red = img_as_float(io.imread('247010 vim-g lamp2-r 20x010/nd_cropc3.tif', as_gray=True))
```

In [3]:
```
img_blue.dtype
```

Out[3]:
```
dtype('float64')
```

tifffile.imread

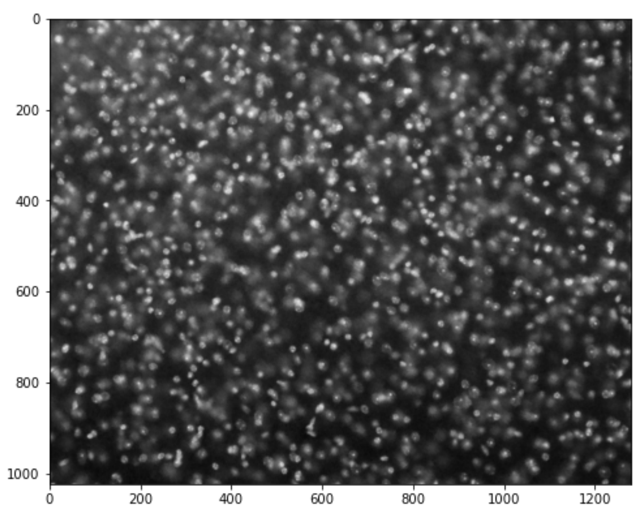
In [4]:
```
ch1 = imread('247010 vim-g lamp2-r 20x010/nd_cropc1.tif').astype(np.float64)
```

In [5]:
```
ch1.dtype
```

Out[5]:
```
dtype('float64')
```

2) Visualize image

In [6]:
```
plt.figure(figsize = (8,8))
plt.imshow(img_blue, cmap="gray");

# cannot view the one imported with tifffile.imread
```



3) Denoise Non_local means algorithm

let's first try to estimate the sigma

In [7]:
```
sigma_est = np.mean(estimate_sigma(img_blue, multichannel=False))
sigma_est
```

Out[7]:
```
0.0002863179066878383
```

apply Non_local means algorithm

In [8]:
```
img_blue_denoised = denoise_nl_means(img_blue, h=2 * sigma_est, fast_mode=True,
                               patch_size=3, patch_distance=5, multichannel=False)
```

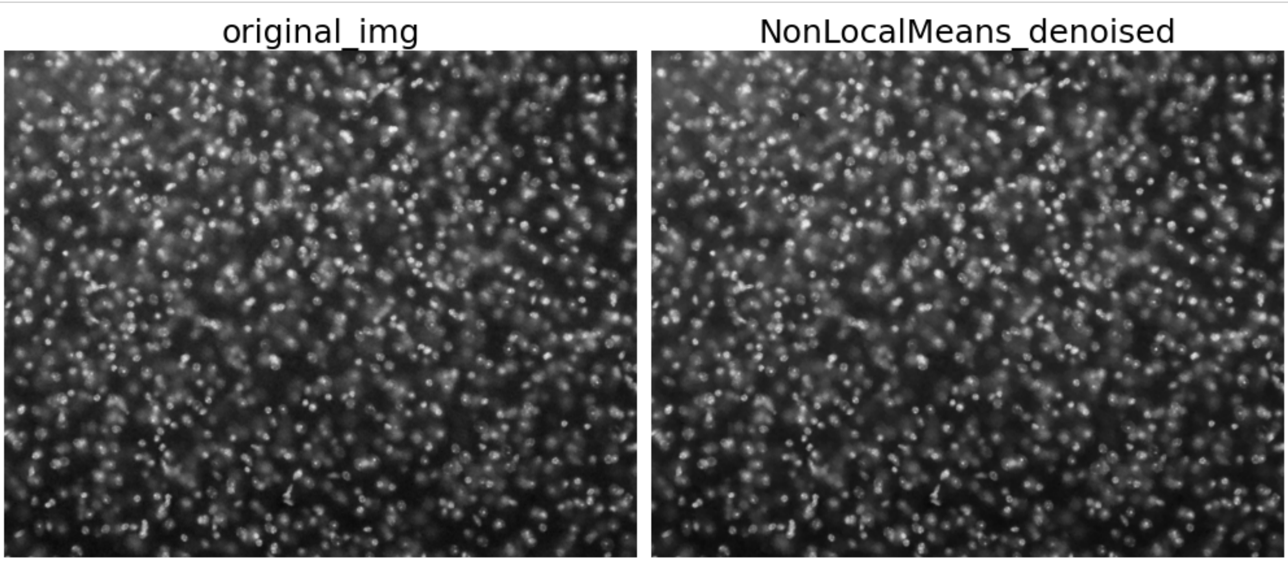
When the fast_mode argument is **False**, a spatial Gaussian weighting is applied to the patches when computing patch distances.

When fast_mode is **True** a faster algorithm employing uniform spatial weighting on the patches is applied.

Larger h allows more smoothing between disimilar patches.

View images side-by-side

In [9]:
```
##let's view original vs NonLocalMeans_filtered
fig, axes = plt.subplots(nrows=1, ncols=2, sharex=True, sharey=True,
                         figsize=(14, 14))
ax = axes.ravel()
ax[0].imshow(img_blue, cmap=plt.cm.gray)
ax[0].set_title('original_img', fontsize=25)
ax[1].imshow(img_blue_denoised , cmap=plt.cm.gray)
ax[1].set_title('NonLocalMeans_denoised', fontsize=25)
for a in ax:
    a.axis('off')
plt.tight_layout()
plt.show();
```



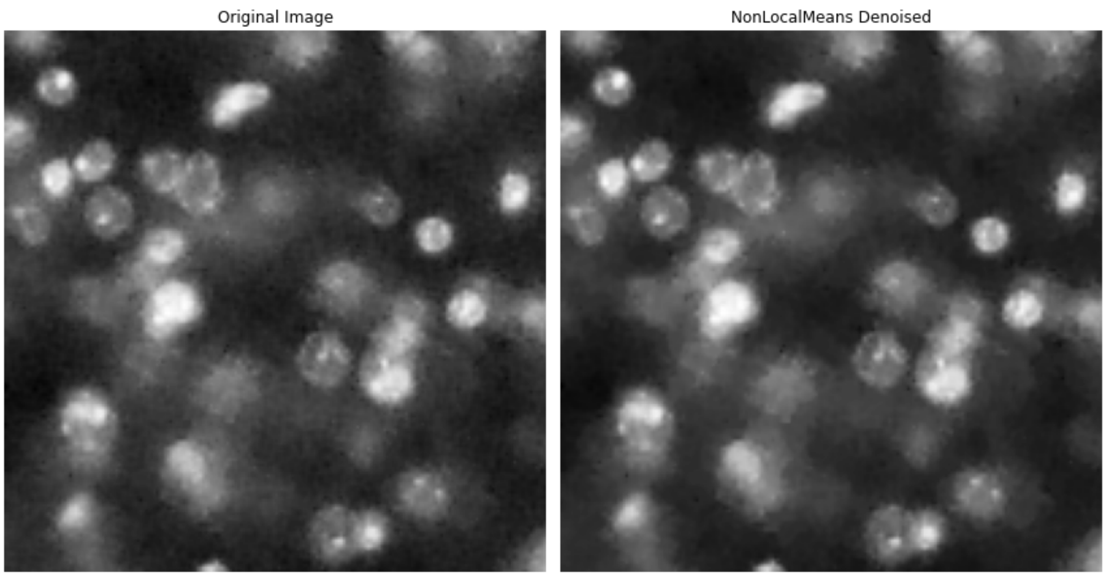
Save image

In [10]:
```
io.imsave(fname="247010 vim-g lamp2-r 20x010/img_blue_denoised.tif", arr=img_blue_denoised)

#plt.imsave("img_green_denoised.tiff", img_blue_denoised, cmap='gray')
```

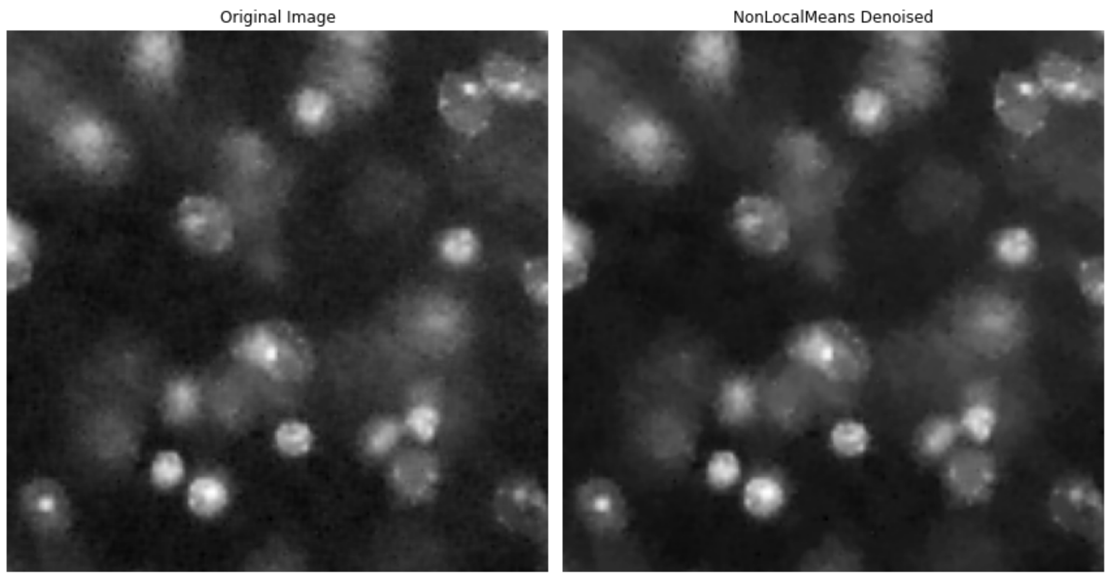
```
C:\Users\mdp18pm\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: UserWarning: 247010 vim-g lamp2-r 20x010/img_blue_denoised.
tif is a low contrast image
  """Entry point for launching an IPython kernel.
```

I show cropped regions to better check for image improvement

In [25]:
```
cropped_img_blue3 = img_blue[250:450, 250:450]
cropped_NonLocalMeans = img_blue_denoised[250:450, 250:450]



# plot figures
fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(12, 12),
                       sharex=True, sharey=True)
plt.gray()
ax[0].imshow(cropped_img_blue3)
ax[0].axis('off')
ax[0].set_title('Original Image')
ax[1].imshow(cropped_NonLocalMeans)
ax[1].axis('off')
ax[1].set_title('NonLocalMeans Denoised')
fig.tight_layout()
plt.show()
```

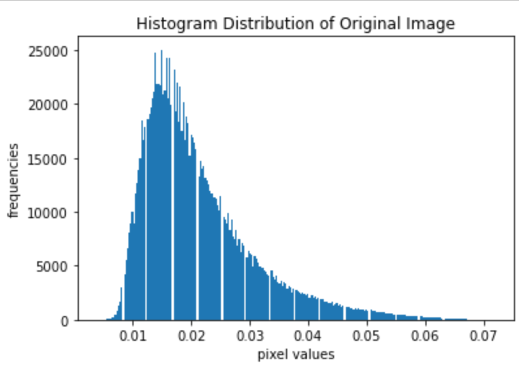


In [12]:
```
cropped_img_blue3 = img_blue[550:750, 550:750]
cropped_NonLocalMeans = img_blue_denoised[550:750, 550:750]



# plot figures
fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(12, 12),
                       sharex=True, sharey=True)
plt.gray()
ax[0].imshow(cropped_img_blue3)
ax[0].axis('off')
ax[0].set_title('Original Image')
ax[1].imshow(cropped_NonLocalMeans)
ax[1].axis('off')
ax[1].set_title('NonLocalMeans Denoised')
fig.tight_layout()
plt.show()
```

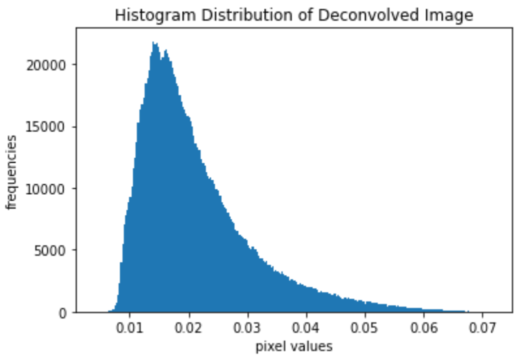


Let's also check whether there are any improvements in the Histograms (showing pixel distribution)

In [13]:
```
ax = plt.hist(img_blue.ravel(), bins = 256)

# Add title and axis names
plt.title('Histogram Distribution of Original Image')
plt.xlabel('pixel values')
plt.ylabel('frequencies')

plt.show()
```



In [14]:
```
ax = plt.hist(img_blue_denoised.ravel(), bins = 256)

# Add title and axis names
plt.title('Histogram Distribution of Deconvolved Image')
plt.xlabel('pixel values')
plt.ylabel('frequencies')

plt.show()
```



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4) Another method for improving the quality of the image: Image Deconvolution

[https://scikit-image.org/docs/dev/auto_examples/filters/plot_restoration.html (https://scikit-image.org/docs/dev/auto_examples/filters/plot_restoration.html)](https://scikit-image.org/docs/dev/auto_examples/filters/plot_restoration.html)

In this example, we deconvolve a noisy version of an image using Wiener and unsupervised Wiener algorithms. This algorithms are based on linear models that can't restore sharp edge as much as non-linear methods (like TV restoration) but are much faster.

Wiener filter

The inverse filter based on the PSF (Point Spread Function), the prior regularisation (penalisation of high frequency) and the tradeoff between the data and prior adequacy. The regularization parameter must be hand tuned.

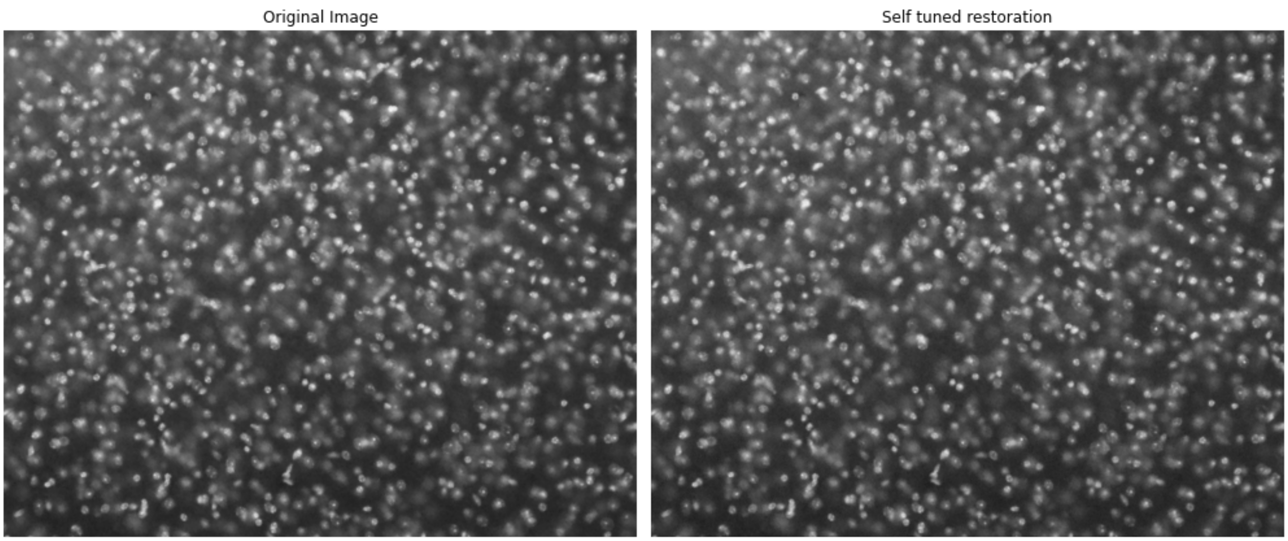
Unsupervised Wiener

This algorithm has a self-tuned regularisation parameters based on data learning. This is not common and based on the following publication [1]_. The algorithm is based on a iterative Gibbs sampler that draw alternatively samples of posterior conditional law of the image, the noise power and the image frequency power.

.. [1] François Orieux, Jean-François Giovannelli, and Thomas Rodet, "Bayesian estimation of regularization and point spread function parameters for Wiener-Hunt deconvolution", J. Opt. Soc. Am. A 27, 1593-1607 (2010)

In [15]:
```
import numpy as np
import matplotlib.pyplot as plt

from skimage import color, data, restoration

#astro = color.rgb2gray(data.astronaut())
from scipy.signal import convolve2d as conv2
psf = np.ones((3, 3)) / 9   #can also try ((3,3))/9
img_blue_conv = conv2(img_blue, psf, 'same')
img_blue_conv += 0.1 * img_blue_conv.std() * np.random.standard_normal(img_blue_conv.shape)

deconvolved, _ = restoration.unsupervised_wiener(img_blue_conv, psf)
```

In [16]:
```
fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(14, 14),
                       sharex=True, sharey=True)

plt.gray()

ax[0].imshow(img_blue, vmin=deconvolved.min(), vmax=deconvolved.max())
ax[0].axis('off')
ax[0].set_title('Original Image')

ax[1].imshow(deconvolved)
ax[1].axis('off')
ax[1].set_title('Self tuned restoration')

fig.tight_layout()

plt.show()
```



In [17]:
```
deconvolved.dtype
```

Out[17]:
```
dtype('float64')
```

save Deconvolved image

In [18]:
```
io.imsave(fname="247010 vim-g lamp2-r 20x010/img_blue_deconvolved.tif", arr=deconvolved)
```

```
C:\Users\mdp18pm\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: UserWarning: 247010 vim-g lamp2-r 20x010/img_blue_deconvolv
ed.tif is a low contrast image
  """Entry point for launching an IPython kernel.
```

Show cropped images for better comparison

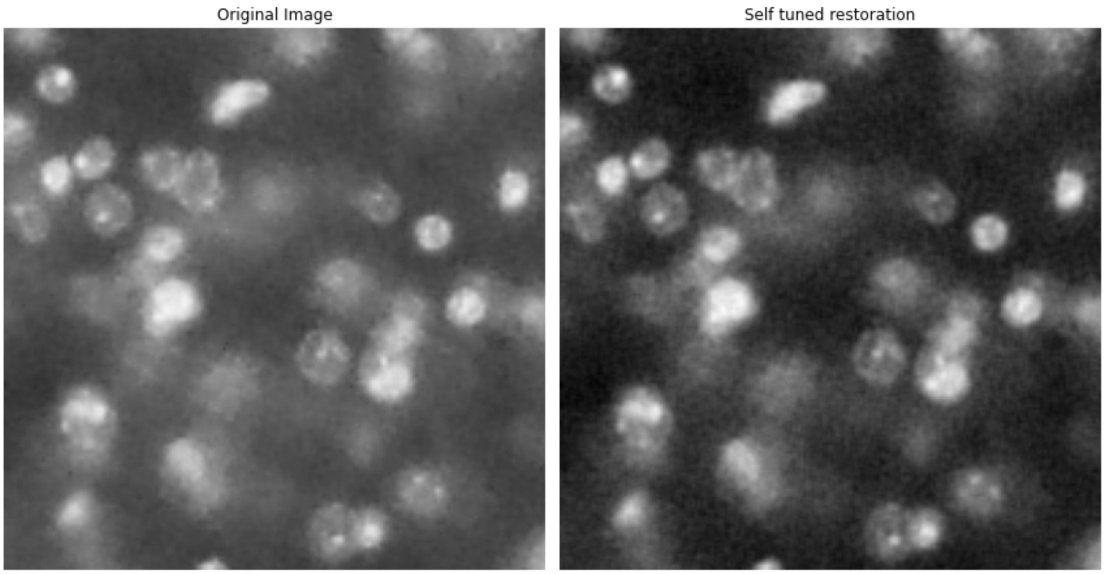
In [19]:
```
img_blue.shape
```

Out[19]:
```
(1024, 1280)
```

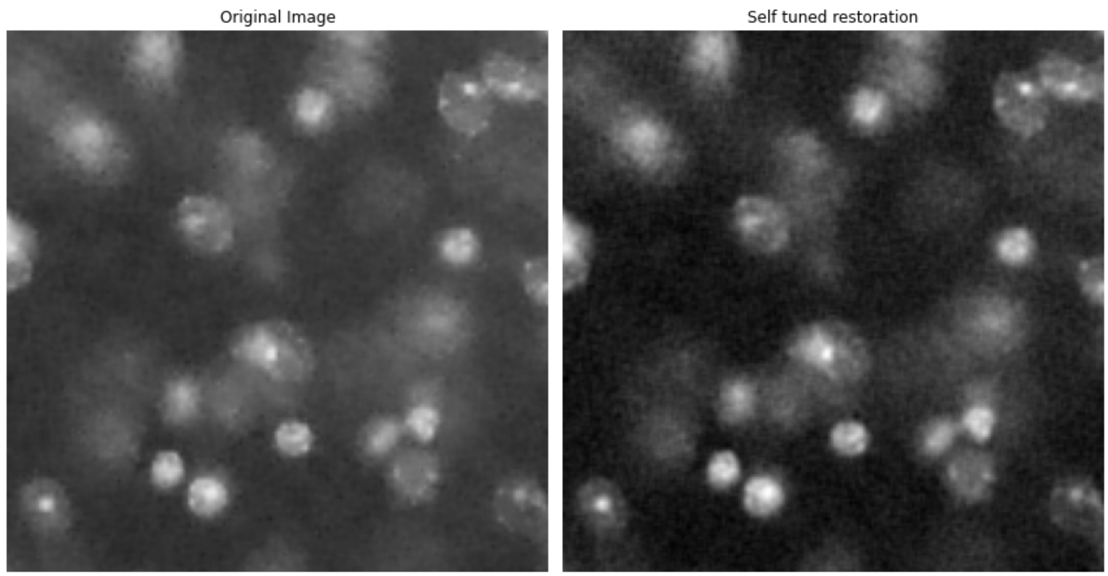
In [20]:
```
deconvolved.shape
```

Out[20]:
```
(1024, 1280)
```

In [21]:
```
cropped_img_blue = img_blue[250:450, 250:450]
cropped_deconvolved = deconvolved[250:450, 250:450]



# plot figures
fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(12, 12),
                       sharex=True, sharey=True)
plt.gray()
ax[0].imshow(cropped_img_blue, vmin=deconvolved.min(), vmax=deconvolved.max())
ax[0].axis('off')
ax[0].set_title('Original Image')
ax[1].imshow(cropped_deconvolved)
ax[1].axis('off')
ax[1].set_title('Self tuned restoration')
fig.tight_layout()
plt.show()
```



In [22]:
```
cropped_img_blue2 = img_blue[550:750, 550:750]
cropped_deconvolved2 = deconvolved[550:750, 550:750]



# plot figures
fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(12, 12),
                       sharex=True, sharey=True)
plt.gray()
ax[0].imshow(cropped_img_blue2, vmin=deconvolved.min(), vmax=deconvolved.max())
ax[0].axis('off')
ax[0].set_title('Original Image')
ax[1].imshow(cropped_deconvolved2)
ax[1].axis('off')
ax[1].set_title('Self tuned restoration')
fig.tight_layout()
plt.show()
```



Comments

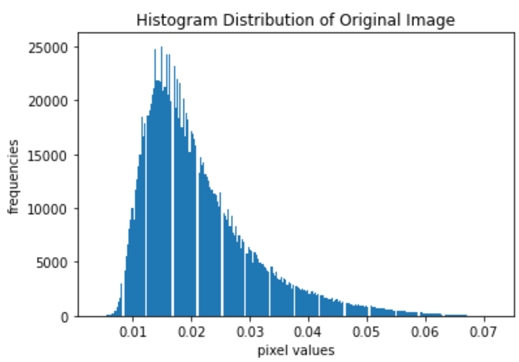
The results of the Deconvolution Wiener filter are very promising despite it does not look like that at a first glance. It's much better noticable in the cropped images.

The generated image has an histogram distribution of pixels which is quite impressively improved compared to the original image.

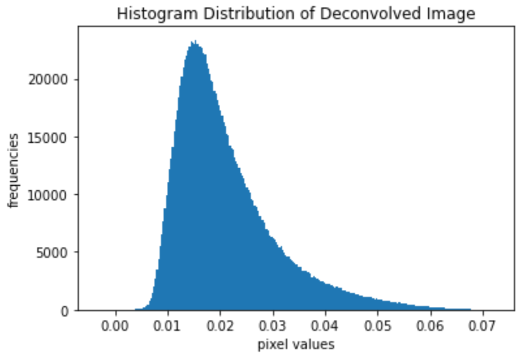
The much better distribution of pixels allows to further manipulate (for example in FIJI as well) the contrast, subtraction of backgroun and sharpening.

Check histograms to further show the nice improvement

In [23]:
```
ax = plt.hist(img_blue.ravel(), bins = 256)

# Add title and axis names
plt.title('Histogram Distribution of Original Image')
plt.xlabel('pixel values')
plt.ylabel('frequencies')

plt.show()
```



In [24]:
```
ax = plt.hist(deconvolved.ravel(), bins = 256)

# Add title and axis names
plt.title('Histogram Distribution of Deconvolved Image')
plt.xlabel('pixel values')
plt.ylabel('frequencies')

plt.show()
```



In [ ]:

In [ ]: