EVROPSKÁ UNIE
Evropské strukturální a investiční fondy
Operační program Výzkum, vývoj a vzdělávání

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KKY/USVP 3

In [70]:

```
%pylab inline
```

```
Populating the interactive namespace from numpy and matplotlib
```

Fourier Transform

In [71]:

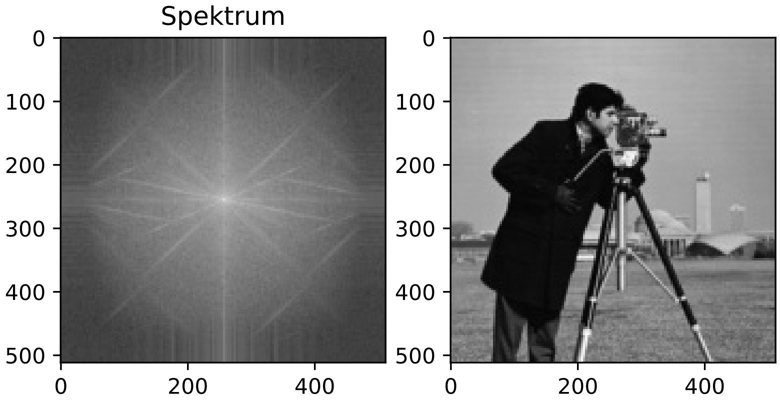
```
import numpy as np
import matplotlib.pyplot as plt
from skimage import data
import skimage.io
import skimage.transform
from operator import itemgetter
```

In [72]:

```
im = data.camera()

ft = np.fft.fft2(im) # 2D Fourier Transform (FT)
ftshift = np.fft.fftshift(ft) # Change quadrants of the FT (1<-->3, 2<-->4)
spek = 20*np.log(np.abs(ftshift)) # Spectrum of FT

# vizualizace
plt.subplot(121)
plt.imshow(spek, cmap = 'gray')
plt.title('Spektrum')

plt.subplot(122)
plt.imshow(im, cmap='gray')
```

Out[72]:

```
<matplotlib.image.AxesImage at 0x7fd3d5ccd7b8>
```



Example of Fourier transfrom application - scan document deskew algorithm

In [73]:

```
def deskew_fft(image, range_min=-15, range_max=15, height=2.0, width=3.0):
    """
```

```
        Function deskew_fft search in the spectrum centre for the skew angle of the image

        @param image - input image
        @param range_min - minimum searched angle (range_min * 0.1 == angle in degrees, this -15 --> -1.5)
        @param range_max - maximum searched angle (range_max * 0.1 == angle in degrees, this  15 -->  1.5)
        @param height - image_height/height -- shrink value of spectrum width
        @param width - image_width/width -- shrink value of spectrum width

        @output Found angle
    """
    ft = np.fft.fft2(image)
    ftshift = np.fft.fftshift(ft)
    spek = 20 * np.log(np.abs(ftshift))
    # spectrum center -- it is not efficient to search in whole spectrum
    spect_cent_y = np.uint32(spek.shape[0]/2)
    spect_cent_x = np.uint32(spek.shape[1]/2)
    spect_offset_y = np.uint32(spek.shape[0]/height)
    spect_offset_x = np.uint32(spek.shape[1]/width)
    spect_center = spek[spect_cent_y-spect_offset_y:spect_cent_y+spect_offset_y,
                        spect_cent_x-spect_offset_x:spect_cent_x+spect_offset_x]
    # Search for max response in spect center
    maxS = 0
    angle = 0
    for i in range(range_min, range_max):
        imr = skimage.transform.rotate(spect_center, i*0.1)
        temp = np.max(np.sum(imr,0))
        if temp > maxS:
            maxS = temp
            angle = i*0.1
    return angle

def rotate(image, angle):
    """
        Function rotate perform image rotation around center by value "angle"

        @param image - input image
        @param angle - rotation angle

        @output - rotated image
    """
    # Creation of bigger image with mean value
    temp_image = np.ones([image.shape[0] * 2, image.shape[1] * 2], dtype=np.uint8) * np.mean(image)
    ymin = int(temp_image.shape[0] / 2.0 - image.shape[0] / 2.0)
    ymax = int(temp_image.shape[0] / 2.0 + image.shape[0] / 2.0)
    xmin = int(temp_image.shape[1] / 2.0 - image.shape[1] / 2.0)
    xmax = int(temp_image.shape[1] / 2.0 + image.shape[1] / 2.0)
    temp_image[ymin: ymax, xmin: xmax] = image
    # Apply rotation
    temp_image = skimage.transform.rotate(temp_image, angle)
    image = temp_image[ymin: ymax, xmin: xmax]
    return image

def deskew(image, y_res=(16, 48), x_res=(10, 20), tiles_perct=0.2):
    """
        Function deskew perform searching for angle in multiple tiles of the image

        @param image - input image
        @param y_res - border and tile size y
        @param x_res - border and tile size x
        @param tiles_perct - percentage of tiles that is used for angle searching
    """
    tiles = []
    border_y = int(image.shape[0]/y_res[0])
    border_x = int(image.shape[1]/x_res[0])
    tile_height = int(image.shape[0]/y_res[1])
    tile_width = int(image.shape[1]/x_res[1])
    for y in range(0 , image.shape[0] - border_y, tile_height):
        y2 = y + border_y
        for x in range(0, image.shape[1] - border_x, tile_width):
            x2 = x + border_x
            tiles.append((y, y2, x, x2, np.mean(image[y:y2, x:x2])))
    tiles.sort(key=itemgetter(4))
    n = int(len(tiles)*tiles_perct)
    angle_mean = 0
    angle = 0
    for i in range(n):
        y = tiles[i][0]
        y2 = tiles[i][1]
        x = tiles[i][2]
        x2 = tiles[i][3]
        part = image[y:y2, x:x2]

        angle = deskew_fft(part)
        angle_mean = angle_mean + angle
    return angle_mean/ float(n)

def apply_deskew(image):
    """
        Function apply_deskew applies deskew algorithm

        @param image - input image
        @output image_deskew - rotated image
        @output angle - found angle
    """
    angle = 0.0
    if len(image.shape) == 2:
        angle = deskew(image)
        image_deskew = rotate(image, angle)
    elif len(image.shape) == 3:
        angle_r = deskew(image[:, :, 0])
        angle_g = deskew(image[:, :, 1])
        angle_b = deskew(image[:, :, 2])
        angle = (angle_r + angle_g + angle_b)/3.0
        image_deskew_r = rotate(image[:, :, 0], angle)
        image_deskew_g = rotate(image[:, :, 1], angle)
        image_deskew_b = rotate(image[:, :, 2], angle)
        image_deskew = np.dstack([image_deskew_r, image_deskew_g, image_deskew_b])
    else:
        print("Vstup musi byt RGB nebo sedotonovy obraz")
    return image_deskew, angle
```

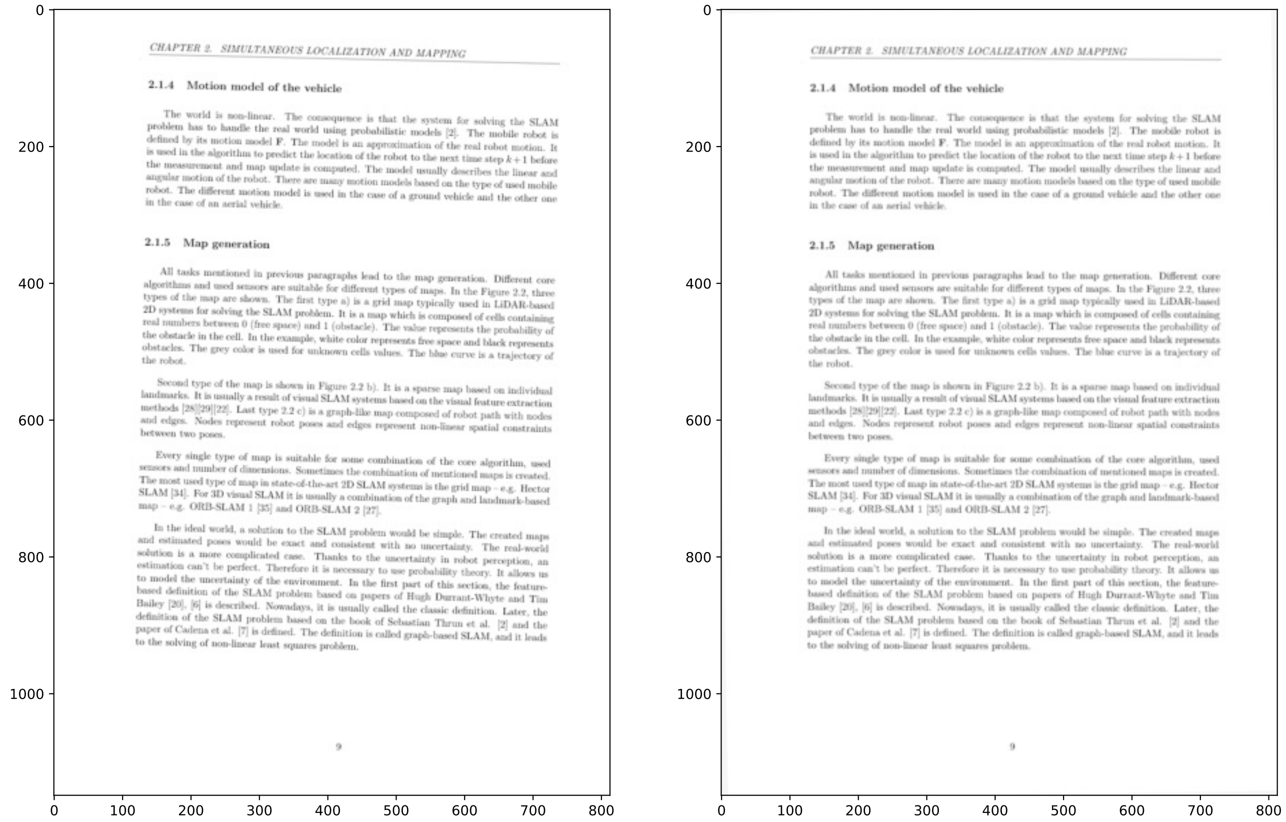
In [74]:

```
skewed_scan = skimage.io.imread("./cviceni_3/download.png", as_gray=True)
deskewed_scan, angle = apply_deskew(skewed_scan)
print(angle)

plt.figure(1, figsize=(16,16))
plt.subplot(121)
plt.imshow(skewed_scan, cmap = 'gray')
plt.subplot(122)
plt.imshow(deskewed_scan, cmap = 'gray')
```

```
1.035393258426969
```

Out[74]:

```
<matplotlib.image.AxesImage at 0x7fd3d5c1eba8>
```



CHAPTER 2. SIMULTANEOUS LOCALIZATION AND MAPPING

2.1.4 Motion model of the vehicle

The world is non-linear. The consequence is that the system for solving the SLAM problem has to handle the real world using probabilistic models [2]. The mobile robot is defined by its motion model **F**. The model is an approximation of the real robot motion. It is used in the algorithm to predict the location of the robot to the next time step $k+1$ before the measurement and map update is computed. The model usually describes the linear and angular motion of the robot. There are many motion models based on the type of used mobile robot. The different motion model is used in the case of a ground vehicle and the other one in the case of an aerial vehicle.

2.1.5 Map generation

All tasks mentioned in previous paragraphs lead to the map generation. Different core algorithms and used sensors are suitable for different types of maps. In the Figure 2.2, three types of the map are shown. The first type a) is a grid map typically used in LiDAR-based 2D systems for solving the SLAM problem. It is a map which is composed of cells containing real numbers between 0 (free space) and 1 (obstacle). The value represents the probability of the obstacle in the cell. In the example, white color represents free space and black represents obstacles. The grey color is used for unknown cells values. The blue curve is a trajectory of the robot.

Second type of the map is shown in Figure 2.2 b). It is a sparse map based on individual landmarks. It is usually a result of visual SLAM systems based on the visual feature extraction methods [28][29][22]. Last type 2.2 c) is a graph-like map composed of robot path with nodes and edges. Nodes represent robot poses and edges represent non-linear spatial constraints between two poses.

Every single type of map is suitable for some combination of the core algorithm, used sensors and number of dimensions. Sometimes the combination of mentioned maps is created. The most used type of map in state-of-the-art 2D SLAM systems is the grid map – e.g. Hector SLAM [34]. For 3D visual SLAM it is usually a combination of the graph and landmark-based map – e.g. ORB-SLAM 1 [35] and ORB-SLAM 2 [27].

In the ideal world, a solution to the SLAM problem would be simple. The created maps and estimated poses would be exact and consistent with no uncertainty. The real-world solution is a more complicated case. Thanks to the uncertainty in robot perception, an estimation can't be perfect. Therefore it is necessary to use probability theory. It allows us to model the uncertainty of the environment. In the first part of this section, the feature-based definition of the SLAM problem based on papers of Hugh Durrant-Whyte and Tim Bailey [20], [6] is described. Nowadays, it is usually called the classic definition. Later, the definition of the SLAM problem based on the book of Sebastian Thrun et al. [2] and the paper of Cadena et al. [7] is defined. The definition is called graph-based SLAM, and it leads to the solving of non-linear least squares problem.

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Mathematical Morphology

Dilation

In [75]:

```python
import numpy as np

def dilate(image, element):
    """
        Binary dilation function

        @param image - input image
        @param element - element
    """
    result = np.zeros(image.shape, dtype=np.uint8)
    indexes = np.where(image == 1)
    elements = np.where(element == 1)
    for y,x in zip(indexes[0], indexes[1]):
        res0 = y + elements[0]
        res1 = x + elements[1]
        result[res0, res1] = 1
    return result
```

Example

In [76]:

```
img = np.zeros([7,7])
img[2:4,2:3] = 1
print(img)

elem = np.zeros([2,2])
elem[:,0] = 1
elem[1,1] = 1

print(elem)

res_im = dilate(img, elem)
print(res_im)
```

```
[[0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 1. 0. 0. 0. 0.]
 [0. 0. 1. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0.]]
[[1. 0.]
 [1. 1.]]
[[0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0]
 [0 0 1 0 0 0 0]
 [0 0 1 1 0 0 0]
 [0 0 1 1 0 0 0]
 [0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0]]
```

Erosion

In [77]:

```
def erode(image, element):
    """
        Binary erosion function

        @param image - input image
        @param element - element
    """
    result = np.zeros(image.shape, dtype=np.uint8)
    indexes = np.where(image == 1)
    elements = np.where(element == 1)
    for y,x in zip(indexes[0], indexes[1]):
        res = [1 - item for item in image[y+elements[0], x+elements[1]].ravel()]
        if(sum(res) == 0):
            result[y, x] = 1
    return result
```

Example

In [78]:

```
erosion_res = erode(res_im, elem)
print(erosion_res)
```

```
[[0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0]
 [0 0 1 0 0 0 0]
 [0 0 1 0 0 0 0]
 [0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0]]
```

Opening and Closing

In [79]:

```python
def morph_open(image, elem):
    """
        Binary opening function

        @param image - input image
        @param element - element
    """
    res1 = erode(image, elem)
    res2 = dilate(res01, elem)
    return res2

def morph_close(image, elem):
    """
        Binary closing function

        @param image - input image
        @param element - element
    """
    res1 = dilate(image, elem)
    res2 = erode(res01, elem)
    return res2
```