# Challenge 6

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## 1 Objectives

Using Python and some libraries like numpy and scipy (listed in the fifth section), we detected interesting corner-like keypoints in a pair of images and proceeded to automatically find the brute-force matches using a window surrounding each keypoint as descriptor.

## 2 Data Acquisition

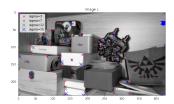
Images were acquired using the camera of a Xiaomi Redmi 5 Plus, and downscaled using local averaging to a third of the original sizes (to a 240x427 shape). The two employed images can be seen in Figure 1.



Figure 1: Captured pair of images for the exercise.

#### 3 Procedure

Following the Harris detector principles exposed in the course notes, the Python code attached in the next section was implemented to find corner keypoints of the gray-scale version of the two taken images. The resulting keypoints for each of a set of four different analysed scales can be found in Figure 2. The markers indicating the keypoints have a size proportional to the scale of the Harris detector that found them. The scales are found in the legend of the figure.



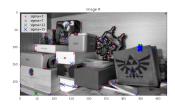


Figure 2: Detected keypoints with the implemented Harris detector for several different pixel scales, which can be found in the legend.

Then, each keypoint is attributed a descriptor of its locality, as a coloured window with a fixed size (the employed parameters can be found in the code section). The pairwise Euclidean distance matrix for all the keypoints in one

image relative to the keypoints of the other image are computed. Then, for each keypoint in one image, its matching keypoint of the other image is selected as the one with the smallest descriptor Euclidean distance to it. The resulting pair of associations can be found in Figure 3.

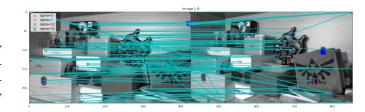


Figure 3: Suggested matches for the keypoints in the two images, using a brute force minimization of the local window descriptor.

In order to filter the results, we then iterate over the matches and only leave those with a matching Euclidean distance for the local window bigger than a certain threshold, and an Euclidean distance in terms of keypoint pixel positions that is smaller than another certain threshold.

#### 4 Results

The resulting keypoint matches can be seen in Figure 4.

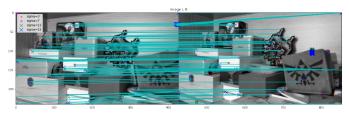


Figure 4: Filtered matches employing the minimized metric for the match and the keypoint index Euclidean distance.

#### References

[1] Class notes.

# 5 Packages

Employed packages and external functions were imported as:

import numpy as np

import cv2

import matplotlib.pyplot as plt

from scipy.signal import convolve2d

import scipy.ndimage

from skimage.transform import

downscale\_local\_mean

from scipy.spatial import distance\_matrix

#### 6 Code

The functions generated for the Harris detector are:

```
gaussian1D(sigma, xmin, xmax, N=None, mu=0):
                           \hbox{if $N$ is $None:}\\
                                      N=int(xmax-xmin +1)
  3
                          4
                           return g/g.sum()
           8
                          max_local_wide=100: if len(im.shape)==3:
 9
                           im = cv2.cvtColor(im, cv2.COLOR_RGB2GRAY)
dx = np.array([[1,0,-1]])/2.0
                           dy = dx.T
 12
                           # compute derivatives
                          # generate metric tensor
                           \verb|im_metric_tens| = \verb|np.dstack| ( [\verb|im_dx**2|, |\verb|im_dy**2|, |\verb|im_dx*im_dy| ) |
                           \mathtt{keypoints} \!=\! \{\}
 19
                           for window_sigma in window_sigmas:
                                      # smoothing using gaussian window
g1D = gaussian1D(window_sigma, -window_sigma*3)
20
21
                                         im_metric_tens_smooth = np.zeros(im.shape+(3,), dtype=np.float64)
                                         for j in range (3):
23
                                                      25
                           symm'),
                                                                                                                                                      g1D[np.newaxis, :], mode='same', boundary='symm')
26
                                         # compute response function to corners
27
                                         \texttt{dets} = \texttt{im\_metric\_tens\_smooth} \, [:\,,:\,,0\,] * \texttt{im\_metric\_tens\_smooth} \, [:\,,:\,,1\,] \, - \, \texttt{im\_metric\_tens\_smooth} \, [:\,,:\,,2\,] * * 2 \, \texttt{mooth} \, [:\,,:\,,2\,] * 2 \, \texttt{mooth} \, [:\,,2\,] * 2 \, \texttt{moot
28
                                         traces = im\_metric\_tens\_smooth[:,:,0] + im\_metric\_tens\_smooth[:,:,1]
 30
                                       R = dets-k*traces**2
31
                                       # detect corners thresholding big positive R values thresholded = (R)=threshold_R)*R
32
33
                                       local_maxima = scipy.ndimage.filters.maximum_filter( thresholded,
34
                                                                                                                                                                    size=(max_local_wide, max_local_wide) ) # size is the size of
35
                          the locality
36
                                       local_max_mask = (thresholded == local_maxima) # convert local max values to binary mask
37
                                         # look for the N biggest R keypoints (most clear ones)
38
                                       \label{eq:normalization} N = \min(\texttt{best\_N\_keypoints}, \ \texttt{np.sum}(\texttt{local\_max\_mask})) \ \# \ \texttt{in} \ \texttt{case} \ \texttt{we} \ \texttt{found} \ \texttt{less} \\ \texttt{best\_indices} = \texttt{np.unravel\_index}(\ \texttt{np.argsort}((\texttt{local\_max\_mask*R}).\texttt{flatten}()) \ [-N:] \ , \ \texttt{shape} = \texttt{np.unravel\_index}(\ \texttt{np.argsort}((\texttt{local\_max\_mask*R}).\texttt{flatten}()) \ [-N:] \ , \ \texttt{shape} = \texttt{np.unravel\_index}(\ \texttt{np.argsort}((\texttt{local\_max\_mask*R}).\texttt{flatten}()) \ [-N:] \ , \ \texttt{shape} = \texttt{np.unravel\_index}(\ \texttt{np.argsort}((\texttt{local\_max\_mask*R}).\texttt{flatten}()) \ [-N:] \ , \ \texttt{shape} = \texttt{np.unravel\_index}(\ \texttt{np.argsort}((\texttt{local\_max\_mask*R}).\texttt{flatten}()) \ [-N:] \ , \ \texttt{shape} = \texttt{np.unravel\_index}(\ \texttt{np.argsort}((\texttt{local\_max\_mask*R}).\texttt{flatten}()) \ [-N:] \ , \ \texttt{shape} = \texttt{np.unravel\_index}(\ \texttt{np.argsort}((\texttt{local\_max\_mask*R}).\texttt{flatten}()) \ [-N:] \ , \ \texttt{shape} = \texttt{np.unravel\_index}(\ \texttt{np.argsort}((\texttt{local\_max\_mask*R})).\texttt{flatten}()) \ [-N:] \ , \ \texttt{shape} = \texttt{np.unravel\_index}(\ \texttt{np.argsort}((\texttt{local\_max\_mask*R}))) \ ]
39
40
                           local_max_mask.shape
41
                                       \label{eq:keypoints} $$ \left[ f'sigma = \left\{ window_sigma \right\}' \right] = np. asarray (best_indices).T \ \#[N, 2 \ (h,w)] $$ $$ $$
42
43
                          return keypoints
```

For obtaining the descriptor local windows:

For the brute force matching:

Then the procedure for the generation of the images was:

```
 \begin{array}{lll} \mathtt{imL\_col} &=& \mathtt{downscale\_local\_mean} \, (\mathtt{cv2.imread} \, (\texttt{"imL.jpg"}) \, [:\, ,:\, ,::\, -1] \, , & \mathtt{factors} \, = (3\,,3\,,1)) \, . \, \mathtt{astype} \, (\mathtt{np.uint8}) \\ \mathtt{imR\_col} &=& \mathtt{downscale\_local\_mean} \, (\mathtt{cv2.imread} \, (\texttt{"imR.jpg"}) \, [:\, ,:\, ,::\, -1] \, , & \mathtt{factors} \, = (3\,,3\,,1)) \, . \, \mathtt{astype} \, (\mathtt{np.uint8}) \\ \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \, , & \mathtt{factors} \, = (3\,,3\,,1)) \, . \, \, \mathtt{astype} \, (\mathtt{np.uint8}) \\ \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \, , & \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \\ \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \, , & \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \\ \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \, , & \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \\ \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \, , & \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \\ \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \, , & \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \\ \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \, , & \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \\ \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \, , & \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \\ \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \, , & \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \\ \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \, ] \, . & \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \\ \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \, ] \, . & \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \, ] \, . \\ \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \, [:\, ,:\, ,::\, -1] \, ] \, . \\ \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \, [:\, ,:\, ,::\, -1] \, ] \, . \\ \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \, [:\, ,:\, ,::\, -1] \, ] \, . \\ \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \, [:\, ,:\, ,::\, -1] \, ] \, . \\ \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \, [:\, ,:\, ,::\, -1] \, [:\, ,:\, ,::\, -1] \, ] \, . \\ \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \, [:\, ,:\, ,::\, -1] \, [:\, ,:\, ,::\, -1] \, ] \, . \\ \mathtt{imR.jpg"} \, (\mathtt{imR.jpg"}) \, [:\, ,:\, ,::\, -1] \, [:\, ,:\, ,::\, -1] \, [:\, ,:\,
                   {\tt imL} = {\tt cv2.cvtColor(imL\_col, cv2.COLOR\_RGB2GRAY}
                   {\tt imR} \ = \ {\tt cv2.cvtColor(imR\_col} \ , \ \ {\tt cv2.COLOR\_RGB2GRAY}
                  plot(np.hstack((imL_col, imR_col)), size=(30,5), save="one.png")
                    \mathtt{sigmas} \, = \, [\, 3 \; , \; \, 7 \, , \; \, 12 \, , \; \, 15 \, ]
                   {\tt keypointsL} = {\tt harris\_keypoints(imL} \,, \,\, {\tt k=0.05} \,, \,\, {\tt window\_sigmas=sigmas} \,, \,\, {\tt threshold\_R=2000} \,, \,\, {\tt t
                                                                                                                                                                                   \verb|best_N_keypoints| = 50, \verb|max_local_wide| = 20)
                  {\tt keypointsR} = {\tt harris\_keypoints(imR, k=0.05, window\_sigmas=sigmas, threshold\_R=2000, window\_sigmas=sigmas, window\_sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigmas=sigma
 10
                                                                                                                                                                                  \texttt{best\_N\_keypoints} = 50, \ \texttt{max\_local\_wide} = 20)
                  sizes = [5, 7, 10, 12]

colors = ['r', 'm', 'g',
                                                                                                                                             'b'
                   fig, axs = plt.subplots(1,2,figsize=(20, 10))
                   axs[0].imshow(imL, cmap='gray')
axs[1].imshow(imR, cmap='gray')
                    for j in range (len(sigmas)):
18
                                           idxs = keypointsL[f'sigma={sigmas[j]}']
                                           axs[0].plot(idxs[:,1], idxs[:,0], 'x', markersize=sizes[j], label=f"sigma={sigmas[j]}", color=colors[j]
20
                                          idxs = keypointsR[f'sigma={sigmas[j]}']
                                          axs[1].plot(idxs[:,1], idxs[:,0], `x', markersize=sizes[j], label=f"sigma={sigmas[j]}", color=colors[j], label=f"sigma={sigmas[j]}", color=colors[j], label=f"sigma={sigmas[j]}", color=colors[j], label=f"sigma={sigmas[j]}", color=colors[j], label=f"sigma={sigmas[j]}", label=f"sigm
22
                   axs \begin{bmatrix} 0 \end{bmatrix}. legend()
                    axs[0].set_title("Image L")
25
                                        [1].legend()
                    axs
                   axs[1].set_title("Image R")
plt.savefig("two.png")
 26
27
28
                   plt.show()
29
30
                     {\tt descriptorsL} = {\tt get\_as\_descriptor\_windows\_around(imL\_col, keypointsL, window\_side} = 51)
                    \tt descriptorsR = get\_as\_descriptor\_windows\_around(imR\_col, keypointsR, window\_side=51)
32
33
                   descriptorsL , descriptorsR = brute_force_matching(descriptorsL , descriptorsR)
34
35
36
                   sizes = [5, 7, 10, 12]
37
                      colors=['r',
                                                                                           'm'
                                                                                                                                              'b'
                   \texttt{fig}\,,\;\; \texttt{axs}\,=\, \texttt{plt.subplots}\,(1\,,\stackrel{.}{1}\,,\texttt{figsize}\,=\!(20\,,\;\;10)\,)
38
39
                     axs.imshow(np.hstack((imL,imR)), cmap='gray')
                    for j in range(len(sigmas)):
40
                                          idxs = keypointsL[f'sigma={sigmas[j]}']
41
                                          axs.plot(idxs[:,1], idxs[:,0], 'x', markersize=sizes[j], color=colors[j])
idxs = keypointsR[f'sigma={sigmas[j]}']
42
                                                                                                 imL.shape[1] + idxs[:,1], idxs[:,0], 'x', markersize = sizes[j], label = f"sigma=\{sigmas[j]\}", color = sigmas[j], label = f"sigmas[j], label = f"sigmas[j
44
                                          axs.plot(
                                           =colors[j])
                                          keypointL, keypointR in zip(descriptorsL['keypoints'], descriptorsL['matches_keypoints']):
axs.plot([keypointL[1], imL.shape[1]+keypointR[1]], [keypointL[0], keypointR[0]], color='c')
45
                   for keypointL,
46
47
                    axs.legend()
                    axs.set_title("Image L R")
49
                   plt.savefig("three.png")
50
                   plt.show()
51
                   # FILTERING
52
                   sizes=[5, 7, 10, 12]
colors=['r', 'm', 'g', 'b']
                                            \mathtt{axs} = \mathtt{plt.subplots} \, (1\,,1\,,\mathtt{figsize} \,{=}\, (20\,,\ 10)\,)
                     axs.imshow(np.hstack((imL,imR)), cmap='gray')
                    for j in range(len(sigmas)):
                                           idxs = keypointsL[f'sigma={sigmas[j]}']
                                          axs.plot(idxs[:,1], idxs[:,0], 'x', markersize=sizes[j], color=colors[j])
idxs = keypointsR[f'sigma={sigmas[j]}']
60
                                                                                               axs.plot(
62
                                           =colors[j])
                   63
64
65
                                          if match_metric <80**2 and keypoint_distance <50**2:
66
                                                            \verb| axs.plot([keypointL[1], imL.shape[1] + keypointR[1]], [keypointL[0], keypointR[0]], color='c')|
67
68
                   axs.legend()
                   axs.set_title("Image L R")
plt.savefig("four.png")
69
70
                   plt.show()
```