

# Noam Salomonski 303161194

## Computer Vision 22928

Explanations for Maman11:

**Please install all requirements with**

pip install -r requirements.txt

with the given requirements.txt

I didn't use any non standard library, but still everything I did use is there.

- The code snippets in this document are simply “where to look at the code”, they have no meaning on their own.
- Github: <https://github.com/noamzilo/OpenUniversityMaman1>

**Question 1:**

Please run **ex1/ex1.py**.

a.

```
generate_random_gaussian_matrix
```

parameters:

```
mean=10, std=5, size=(100, 100)
```

as requested,.

Linearly normalizing the output to be between 0 and 1, so cv2.imshow can work with it. And show it properly.

b.

```
draw_histogram
```

using 256 bins, setting some arbitrary bin width for visual beauty.

Centering each bar on the average of its data by calculating

```
center = (bins[:-1] + bins[1:]) / 2
```

c.

```
read_my_image
```

reading the image twice-

once into

```
self._color_image
```

as a color image

and once into

```
self._grayscale_image
```

as a grayscale image

d.

```
detect_edges
```

applying a canny edge detector by cv2.

Using thresholds: (thres1, thres2) = (300, 250), (500, 300), (1000, 250)

With lower thres1, we see finer details.

With lower thres2 we see lines less broken.

This is given  $\text{thres1} > \text{thres2}$ .

e.

```
def detect_harris(self, block_size, ksize, k,
corner_threshold): # 1e
```

Applying a harris detector by cv2.

Drawing found points on the input image.

As **kSize** increases, the edges seem to get blurry. This is because the sobel kernel becomes larger, and it responds more weakly to sharp (small) edges.

I selected the parameter **k** to 0.04, as an empirical result by several posts online.

A bigger **k** should give less false corners, and more lost true corners. (recall-precision tradeoff).

**Block\_size** is the size of neighborhood to apply Harris for each point. Larger would usually mean the point would be more likely to be selected as a positive corner, given the rest of the parameters remain the same.

**Corner\_threshold** is a threshold to eliminate corners whose value is too low and would qualify as false positives. A larger value corresponds to less corners, and to more confidence in corners that pass.

## Question 2:

Please run **ex2/blob\_detector.py**

THIS TAKES A WHILE. Please let it run, or disable some of the images in main().

The code runs for all input images. For each one:

1. Create a blob detector, which creates pyramids (different sizes of LOG filter) using the given function. It is designed that way to allow image pyramids rather than filter pyramids in the future.

```
pyramids
```

is calculated, which is a  $h \times w \times \text{number of scales}$  matrix.

2. Find local maxima, then suppress non maxima using

```
filters.maximum_filter(pyramids,  
suppression_diameter)
```

with suppression diameter (the diameter in which a maximum has to be absolute) =  $\text{median}(\text{scales})$ . I tried to find some adaptive threshold, so that I wouldn't have to tune it for every image. This choice seemed natural, and not extreme.

Also, throw away all possible maxima that don't pass

```
self._max_min_threshold
```

which I chose as 15, experimentally.

Then draw blobs with their relevant scale on the color image (not the grayscale, because the color is the original).

I chose 15 (the maximum allowed) levels of pyramids because they are then capable of finding the largest blobs.

It can be edited in

```
_set_constants
```

The filter must be normalized by  $\sigma^2$  because its response decreases as  $\sigma$  increases. For each gaussian derivative, the response to shock decreases by a factor of  $\sigma$ . Since Laplacian is a second derivative, we get  $\sigma^2$ .

Non maximum suppression is performed in 3d by

```
scipy.ndimage.filters  
maximum_filter
```

on the requested 3d matrix of pyramids (filters of different scales activated on the original image), one time finding maxima, and one time minima.