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**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 thres1 > 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-percision 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 X w X number of scales matrix.

1. 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) = median(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.