Report

March 6, 2021

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Assignment 1 \label{eq:Assignment} \begin{tabular}{ll} Mohamed A. AbdelHamed - 900163202 \\ oscar@aucegypt.edu \end{tabular}
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1 Part 1:

1.1 Transformation Formats:

```
[1]: from parse_utils import trans_format
    print(trans_format)

Please insert a list of your transformations in the following format:
    <trans_key1 ...args1> <trans_key2 ...args2> ... <trans_key_n ...args_n>

Available transormations:
    <TRANS offset>
    <SCALE Sx Sy>
    <ROT angle(degrees) Px Py>
    <NTHP n>
    <HE>
```

1.2 (a) Matrix transformations:

1.2.1 i. Translations:

```
[2]: import part1
    trans = '<TRANS 50 100>'
    part1.run(interactive=False, img_path='samples/rome.jpg', trans_str=trans,
    →effect='Translated')
```

Original



Translated



1.2.2 ii. Rotation:

```
[3]: import part1
trans = '<ROT 45 250 250>'
part1.run(interactive=False, img_path='samples/rome.jpg', trans_str=trans,

→effect='Rotated')
```

Original



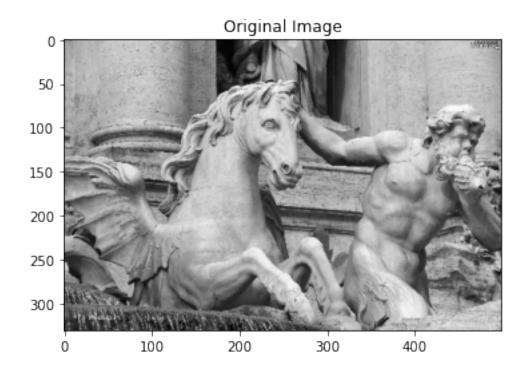
Rotated

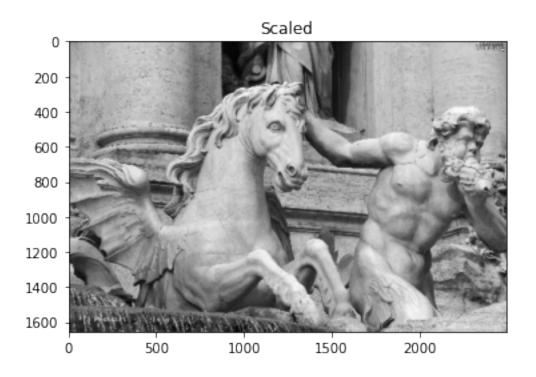


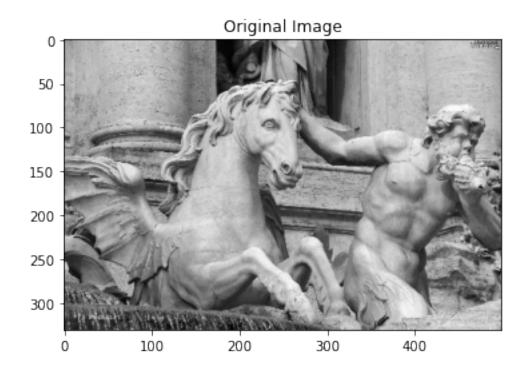
1.2.3 iii. Scaling:

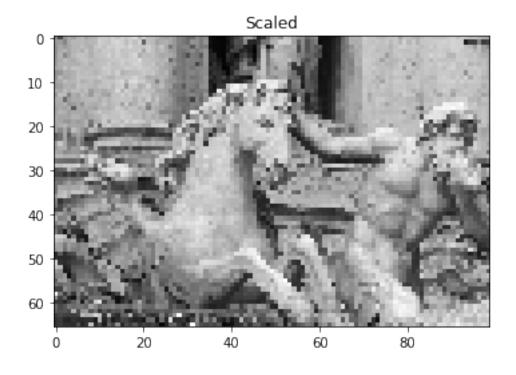
Note the axes values are used to observe new scaling in pixels.

```
[4]: import part1
trans = '<SCALE 5 5>'
part1.run(interactive=False, img_path='samples/rome.jpg', trans_str=trans, 
→effect='Scaled', side_by_side=False)
```







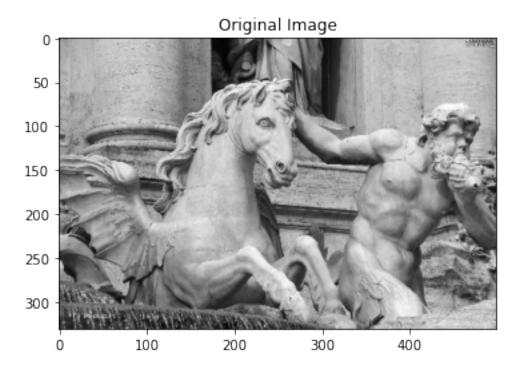


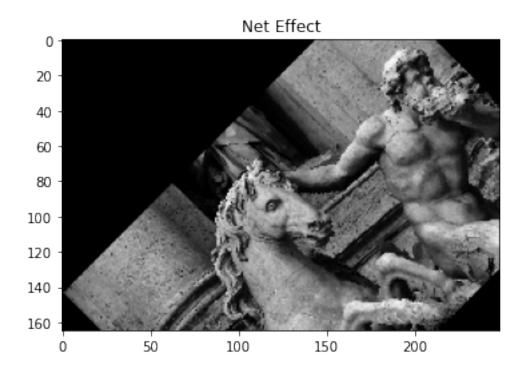
Comments:

- 1. Scaling up does not show notable gaps because the transformation is executed in reverse (i.e. looping over destination pixel instead of source pixels).
- 2. Scaling down clearly reduces image quality due to loss of pixels.

1.2.4 iv. Combined Transformations:

Note that the program also supports mixing transformations with the ones in part b (HE, and n^{th} power).





1.3 (b):

1.3.1 i. n^{th} power:

```
[7]: import part1 trans1 = '<NTHP 5>' part1.run(interactive=False, img_path='samples/rome.jpg', trans_str=trans1)
```

Original





```
[8]: import part1 trans2 = '<NTHP 0.2>'
```

part1.run(interactive=False, img_path='samples/rome.jpg', trans_str=trans2)

Original





1.3.2 ii. Histogram Equalization:

```
[9]: import part1
trans = '<HE>'
part1.run(interactive=False, img_path='samples/he.jpg', trans_str=trans)
```

Original





2 Part 2:

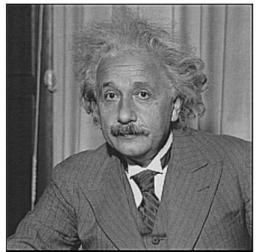
2.1 (a) Smoothing Filter (using averaging):

$$F_{avg} = \frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

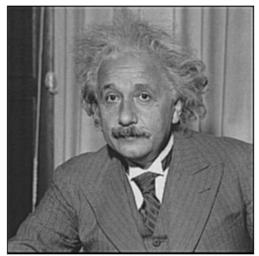
Sample run on a sharpened image:

[10]: from part2 import part_a
part_a()

Original



Smoothed



2.2 (b) Gradient Filter (Laplacian):

$$F_{lap} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & -8 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

Sample run:

[11]: from part2 import part_b
part_b()

Original



Enhanced



Gradient



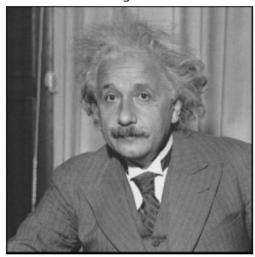
2.3 (c) Sharpening Filter:

$$F_{sharp} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix} - \frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

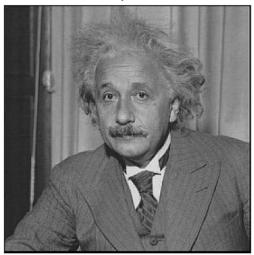
Sample run on smoothed image:

[12]: from part2 import part_c part_c()

Original



Sharpened



Part 3: 3

(a) One other separable filter would be the vertical (or horizontal) Sobel filter for edge detection:

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For our example, we use the vertical edge filter:

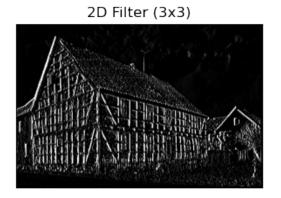
$$F_1 = \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix}$$
, $F_2 = \begin{bmatrix} 1 & 0 & -1 \end{bmatrix}$ such that $F = F_1.F_2$

3.2 (b)

Below are the results comparison for different filter sizes (2D vs. Separated 1D):

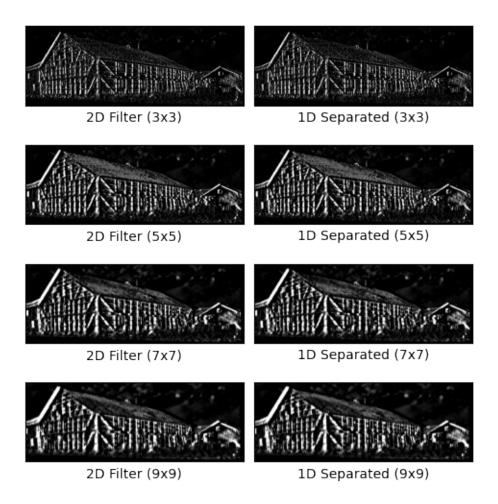
[1]: import part3 part3.run()







2D Filters vs 1D Decomposition



Comments:

- 1. Filtered images are emphasizing the vertical lines as expected.
- 2. For the same filter size, the 1D and 2D filter versions look identical as expected.
- 3. For small filter sizes, program overheads (e.g. loop packing, memory allocation, copying) dominate the performance gain of filter separation until filter size is large enough for the gain to appear.
- 4. The consistency of the trend in (4) is fragile due to high sensitivity in execution time with relatively small filters.