Introduction to Computer Vision – Homework 0
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1 Input images

We consider 4 input images of different sizes (figure 1).

(a) Input p0-1-0.jpg, 207x236 pixels

(b) Input p0-1-1.jpg, 183x275 pixels

(c) Input p0-1-2.jpg, 272x384 pixels

(d) Input p0-1-3.jpg, 390x502 pixels

Figure 1: Input images

2 Color planes

a) Swap the red and blue channels of the input image.

The results are shown in figure 2. The $imread()$ instruction of OpenCV reads images in format BGR, then we have to swap the channel blue(first channel) with the channel red(third channel), generating a new image in RGB format.

b) Create a monochrome image (img-green) by selecting the green channel of the input image.

The results are shown in figure 3. As we extract the green channel from the original image to generate a monochromatic image, then, the regions of the image that depend more on green color will have values close to 255 in the channel green, which means that in the output image those regions will have a color close to white, while the other regions of the image will have a color close to black.

c) Create a monochrome image (img-red) by selecting the red channel of the first input image.

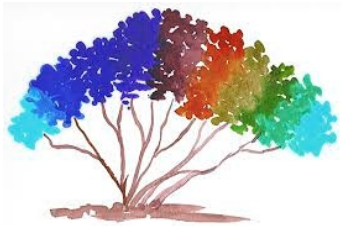
The results are shown in figure 4. Similar to the previous interpretation, we say that the light colored regions in the output image corresponds to regions with high red values in the original image.

d) Which image looks more like what you would expect a monochrome image to look like? Would you expect a computer vision algorithm to work on one better than the other? Why?

The monochrome image generated from the green channel most closely resembles the monochrome image. The intuition behind this effect is that in one of the popular formulas to convert RGB to grayscale images ($R \times 0.29 + G \times 0,58 + B \times 0,11$) the green channel has bigger weighting.

A Computer Vision algorithm would work better in one representation, depending of the image properties, e.g. suppose that we have an image that has lower values in the red channel, thus using a monochromatic representation using this channel has a lot of black areas and this may yield in a worse results. On the hand, using the green channel would make the image more discriminative. Analogously, the same would occurs with an image with low green values.

(a) Output for the input p0-1-0.jpg



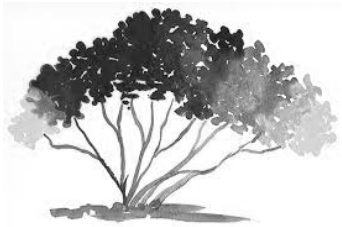
(b) Output for the input p0-1-1.jpg

(c) Output for the input p0-1-2.jpg

(d) Output for the input p0-1-3.jpg

Figure 2: Output images for question 2.a

(a) Output for the input p0-1-0.jpg



(b) Output for the input p0-1-1.jpg

(c) Output for the input p0-1-2.jpg

(d) Output for the input p0-1-3.jpg

Figure 3: Output images for question 2.b

3 Replacements of pixels.

a) Let us call the monochrome image from your answer to the last item of the previous question A , and the other one B . Take the center square region of 100×100 pixels of A and insert it into the center of B.

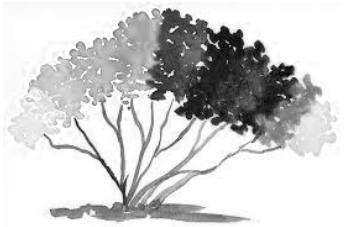
The results are shown in figure 5.

b) Replace the respective channel of B into the original image.

The results are shown in figure 6.

In 3.a the differences are easier to see in the images 5.a, 5.c, in the same occurs in 3.b. This happens because these images presents higher green than red values in its center areas, generating more purple-blue colors which is reflected as darker points in the monochromatic image. In the images 5.b, 5.d, the red colors turn to yellow which is lighter in the monochromatic image.

(a) Figura 13. Output for the input p0-1-0.jpg



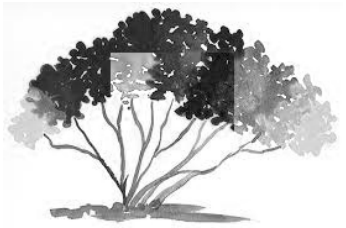
(b) Figura 14. Output for the input p0-1-1.jpg

(c) Figura 15. Output for the input p0-1-0.jpg

(d) Figura 16. Output for the input p0-1-1.jpg

Figure 4: Output images for question 2.c

(a) Output for the input p0-1-0.jpg



(b) Output for the input p0-1-1.jpg

(c) Output for the input p0-1-2.jpg

(d) Output for the input p0-1-3.jpg

Figure 5: Output images for question 3.a

4 Arithmetic and geometric operations.

a) What is the min and max of the values of $img - green$? What is the mean? What is the standard deviation? How do you compute them? Provide code snippets in your report for these questions.

The results for each $img - green$ is summarized on table 1

Img. name	max	min	mean	std. deviation
p0-2-b-0.jpg	255	0	137.844	61.710
p0-2-b-1.jpg	255	0	198.553	76.377
p0-2-b-2.jpg	255	0	137.885	61.294
p0-2-b-3.jpg	255	0	138.209	77.913

Table 1: Summary for image statistics

(a) Output for the input p0-1-0.jpg

(b) Output for the input p0-1-1.jpg

(c) Output for the input p0-1-2.jpg

(d) Output for the input p0-1-3.jpg

Figure 6: Output images for question 3.b

The code snippet for this problem is relative small using python:

```
import numpy as np
def question_A(img):
        img_max = img.max() #image max
        img_min = img.min() #image min
        img_mean = img.sum()/(1. * img.shape[0] * img.shape[1]) #image mean
        img_std = np.std(img.ravel()) #image standard deviation
        print ('max:', img_max, 'min:', img_min, 'mean:', img_mean, 'std:', img_std)
```

b) Normalize the values of img-green. How the image looks like? Do you have an idea of what happened?
The results of the normalization are shown in figure 7.

(a) Output for $img - green$ of p0-1-0.jpg

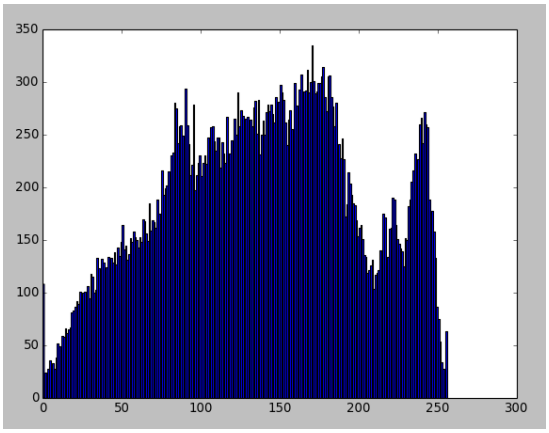
(b) Output for $img - green$ of p0-1-1.jpg

(c) Output for $img - green$ of p0-1-2.jpg

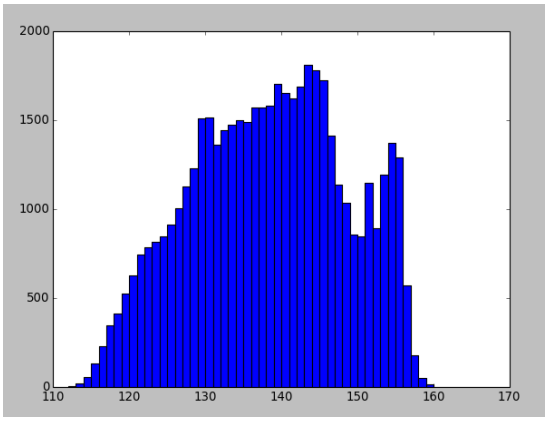
(d) Output for $img - green$ of p0-1-3.jpg

Figure 7: Output images for question 4.b

Comparing this images with the originals, it seems that a gray mask has been applied and edges are less highlighting. The explanation for this effect can be done analysing the histograms that the images generate (figure 8). In the normalized image, the color are centered and goes from a range of $[0, 255]$ to a smaller one, note that the shape of the histograms (visual relation between bins size) remains the same, hence, the normalization works as a operation that push the bins to the center values removing the highest and lowest values.



(a) Histogram for $img - green$ of p0-1-0.jpg



(b) Histogram for norm. $img - green$ of p0-1-1.jpg

Figure 8: Histograms for $img - green$ and its normalizated image

c) Shift img-green to the left by 2 pixels. Store the resulting image in the output folder. Subtract the shifted version to the original, and save the difference image. Make sure that all the values you are saving are legal so you can see all the differences. What do the negative values mean? What do you see in the result?

The results for the shifted image, and the original image subtracted with the shifted are shown in figure 9, the images shifted to left by two pixel present a black line which actually are the parts of the image that were replaced with 0 as part of the shifting. In the case of the subtracted image, an interesting effects occurs: it presents approximation of the edges from the original images. This is really interesting and the min, max, mean and standard deviation (table 2) of the subtracted image can give an intuition of this effect.

Comparing the image statistics, we can see a big effect in the mean: it has decreased widely, since in RGB system a value 0 is equal to black, all the pixel that has negative value are represented with black, and they may represent no-edges, this is because edges are consider as elements with high frequency, thus, when subtracting with an adjacent pixel (shifted image) its value is usually bigger and the result is positive (not black).

Img. name	**max**	**min**	**mean**	**std. deviation**
p0-2-b-0.jpg	232	-211	1.007	46.324
p0-2-b-1.jpg	255	-253	1.830	44.505
p0-2-b-2.jpg	216	-168	0.640	19.299
p0-2-b-3.jpg	239	-234	0.608	43.411

Table 2: Summary for image statistics

5 Noise.

a) Take the original colored image (img) and add Gaussian noise to the pixels in the green channel. Increase the sigma until the noise is visible in the image. Store the image into the output folder. What is the value of sigma you used? How did the noise in the resulting images behave? What did you observe?

The results of adding gaussian noise to the blue channel are shown in figure 10. The value of sigma used is 30, the noise tends to affect black/white-like areas, this is more clean in figures 10.b and 10.d, the noise does affect selective parts of the image.

b) Add the noise using the same sigma to the blue channel instead. Store the output.

The results of adding gaussian noise to the blue channel are shown in figure 11.

c) Which image looks better? Why?

The noise in the blue channel looks better because in the final image it generated points of color yellow that do no have a big contrast with the color around them, on the other hand, the noise in the green channel creates purple points that are more notorious.

(a) Shifted image for input p0-1-0.jpg

(b) Original subtracted with shifted image for p0-1-0.jpg

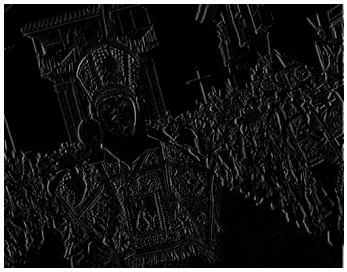
(c) Shifted image for input p0-1-1.jpg

(d) Original subtracted with shifted image for p0-1-1.jpg

(e) Shifted image for input p0-1-2.jpg

(f) Original subtracted with shifted image for p0-1-2.jpg

(g) Shifted image for input p0-1-3.jpg

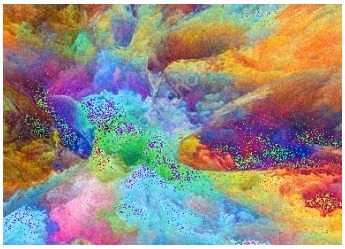


(h) Original subtracted with shifted image for p0-1-3.jpg

Figure 9: Output images for question 4.c

(a) Gaussian noise on p0-1-0.jpg green channel

(b) Gaussian noise on p0-1-1.jpg green channel



(c) Gaussian noise on p0-1-2.jpg green channel

(d) Gaussian noise on p0-1-3.jpg green channel

Figure 10: Gaussian noise on green channel

(a) Gaussian noise on p0-1-0.jpg blue channel

(b) Gaussian noise on p0-1-1.jpg blue channel

(c) Gaussian noise on p0-1-2.jpg blue channel

(d) Gaussian noise on p0-1-3.jpg blue channel

Figure 11: Gaussian noise on blue channel