Computer Vision (Spring 2021) Problem Set #1

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1a. Interesting Images

Image 1 - ps1-1-a-1

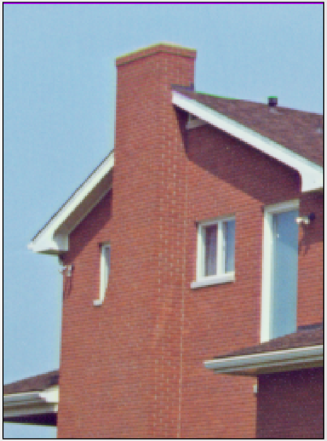

Image 2 - ps1-1-a-2

4d: Difference Image

ps1-4-d-1

5a: Noisy Green Channel

ps1-5-a-1

5b: Noisy Blue Channel

ps1-5-b-1

6a. Discussion

Between all color channels, which channel, in your opinion, most resembles a gray-scale conversion of the original. Why do you think this? Does it matter for each respective image? (For this problem, you will have to read a bit on how the eye works/cameras to discover which channel is more prevalent and widely used)

i. I have used analyze channels.py to analyze the channels of the image (I have uploaded the code as well). It turned out that the green channel most resembles grayscale conversion with the highest correlation (0.9128) compared to blue (0.7408) and red (0.7926). So both visually and numerically, the green channel seems to be the most close to the grayscale.

ii. I found that this is because the green channel is more prevalent and widely used in the eye along with camera sensors. I have found the luminance formula $y = 0.299R + 0.587G + 0.114B$ that seemed to indicate that we are more sensitive to green lights, in general, although I do not fully understand this.

iii. I am not sure if this phenomenon differs for other images, but at least for the images I have tested (the ones used for this assignment), the result was the same; the green channel showed higher similarity to the grayscale. I would argue that, given the theoretical backup in ii, the same result will hold for most images we encounter.

6b. Discussion

What does it mean when an image has negative pixel values stored? Why is it important to maintain negative pixel values?

Negative pixel values indicate normalized image representations (e.g., -1 to 1 range with 0 being the gray) or result from mathematical operations like image subtraction. In these cases, negative values have meanings that should not be simply ignored. Clipping negatives to zero would lose important information about gradients, edges, and relationships between pixels. Clipped values cannot be recovered after all. Negative values might originate from mishandling the data, but one should examine it carefully to understand the exact cause before simply clipping them.

6c. Discussion

In question 5, noise was added to the green channel and also to the blue channel. Which looks better to you? Why? What sigma was used to detect any discernible difference?

i. The green channel (ps1-5-a-1) looked much noisier even with smaller sigma.

ii. I believe this has to do with the result we have derived in 6a. The green channel is used the most by the eye and camera sensors. So adding noise to the green channel will be more noticeable by human eyes.

iii. sigma = 25 was used. The green channel showed noise even with smaller sigma (even below 10), but for the blue channel it started to show comparably visible noise with sigma = 100. The latter still seemed to affect the background the most, not the main human figure.

7a: Hybrid Images

ps1-7-a-1

7b. Hybrid Images

Explain how the cutoff-frequency impacts the final hybrid image

i. I have chosen cutoff frequency = 5. At the given level 7, the cat image dominated at both near and far views. At 6, the dog started to appear only from very far away. At 5, I was able to recognize the cat at a close distance and the dog at a far distance. At 4, the result looked increasingly dog-dominant even up close.

ii. It is as I have explained above. As the cutoff frequency decreased, the low-frequency dog image started to dominate. On the other hand, as the cutoff frequency increased, the high-frequency cat image started to dominate. But in most cases, cat image seemed to be quite prevalent unless the cutoff was very low.