1.8: Lighting and color spaces

I would like to start this lesson by telling a personal story from my time spent developing ID My Pill (http://www.idmypill.com).

For those who are unfamiliar with my previous ventures, ID My Pill is an iPhone application and web API that allows you to identify prescription pills in the snap of your smartphone. You simply snap a photo of your prescription pills and ID My Pill instantly identifies and verifies that they are the correct medication using computer vision and machine learning techniques.

And whether or not a pill is identified ***correctly*** has ***nothing*** to do with the programming language I used to develop it. It has ***nothing*** to do with the computer vision libraries that I built ID My Pill around. And a successful pill identification has ***absolutely nothing*** to do with my pill identification algorithms that I developed working in the background.

In fact, whether or not a pill can be successfully identified is determined long before a ***single line of code*** is even executed.

I'm talking, of course, about ***lighting conditions***.

A pill captured in very poor lighting conditions where there is an abundant amount of shadowing, washout, or lack of contrast simply cannot be identified. With over 27,000+ prescription pills in the market in the United States (with well over half being round and/or white), there are an incredible number of pills that are near identical to each other. And given this high number of visually similar pills,

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Lighting conditions can completely ruin the results of the entire algorithm.

Believe it or not, the success of (nearly) all computer vision systems and applications is determined before the developer writes a single line of code.

In the rest of this article we'll be discussing the importance of lighting conditions and the dramatic role it plays in the successful development of a computer vision system. We'll also be discussing *color spaces* and how we can leverage them to build more robust computer vision applications.

Objectives:

1. Understand the role lighting conditions play in the development of a successful computer vision system.
2. Discuss the four primary color spaces you'll encounter in computer vision: *RGB*, *HSV*, *L*a*b**, and *grayscale* (which isn't *technically* a color space, but is used in many computer vision applications).

Lighting Conditions

The field of computer vision is rapidly expanding and evolving. Every day we are seeing new advances in the field that we once thought were impossible. We're seeing deep learning classify images with astonishingly high accuracy. Tiny little computers, like the Raspberry Pi, can be used to build intricate surveillance systems. And industry is seeing more commercial computer vision applications pushed to market every single day.

And while the field is growing, changing, and evolving, I can guarantee you one absolute constant that will never change: every single computer vision algorithm, application, and system *ever* developed and that *will be* developed will depend on the quality of images input to the system.

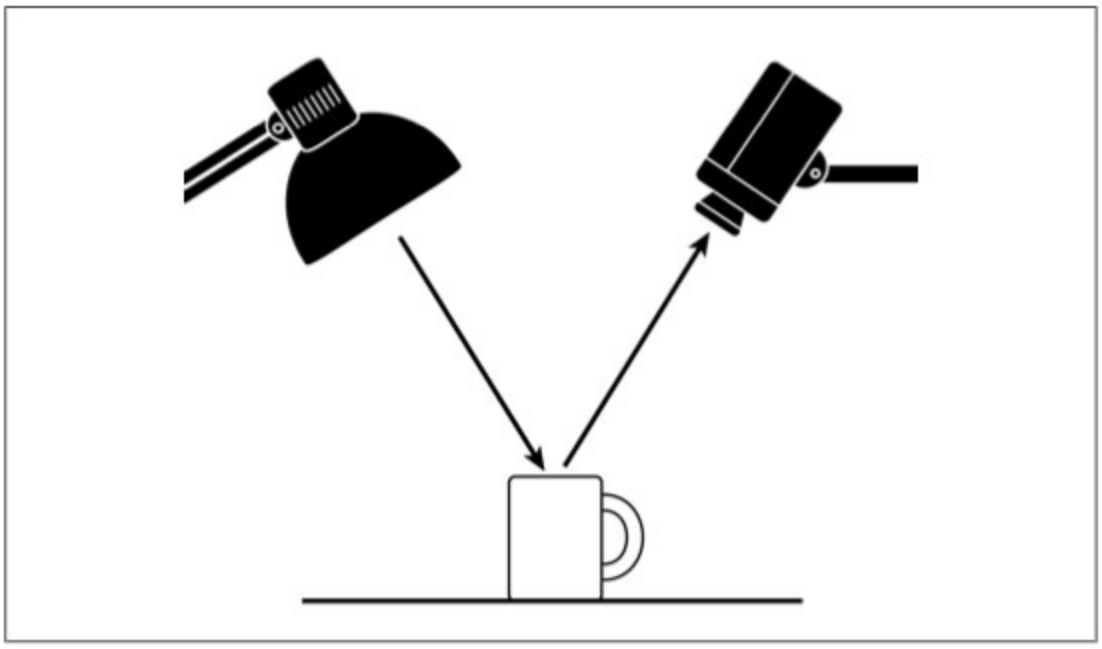
We'll certainly be able to make our systems more *robust* in relation to poor lighting conditions, but we'll never be able to *overcome* an image that was captured under inferior conditions.

So let me say this again, because I really want to make sure it sticks: *lighting can mean the difference between success and failure of your computer vision algorithm*.

One of ***the most common pitfalls*** I see computer vision developers make is overlooking lighting and the effect it will have on algorithm performance.

The quality of light in a given environment is absolutely crucial in obtaining your goals — in fact, I would go as far to say that it is likely ***the most important factor***.

To really demonstrate this fact, consider for a second how a camera captures or films an object:

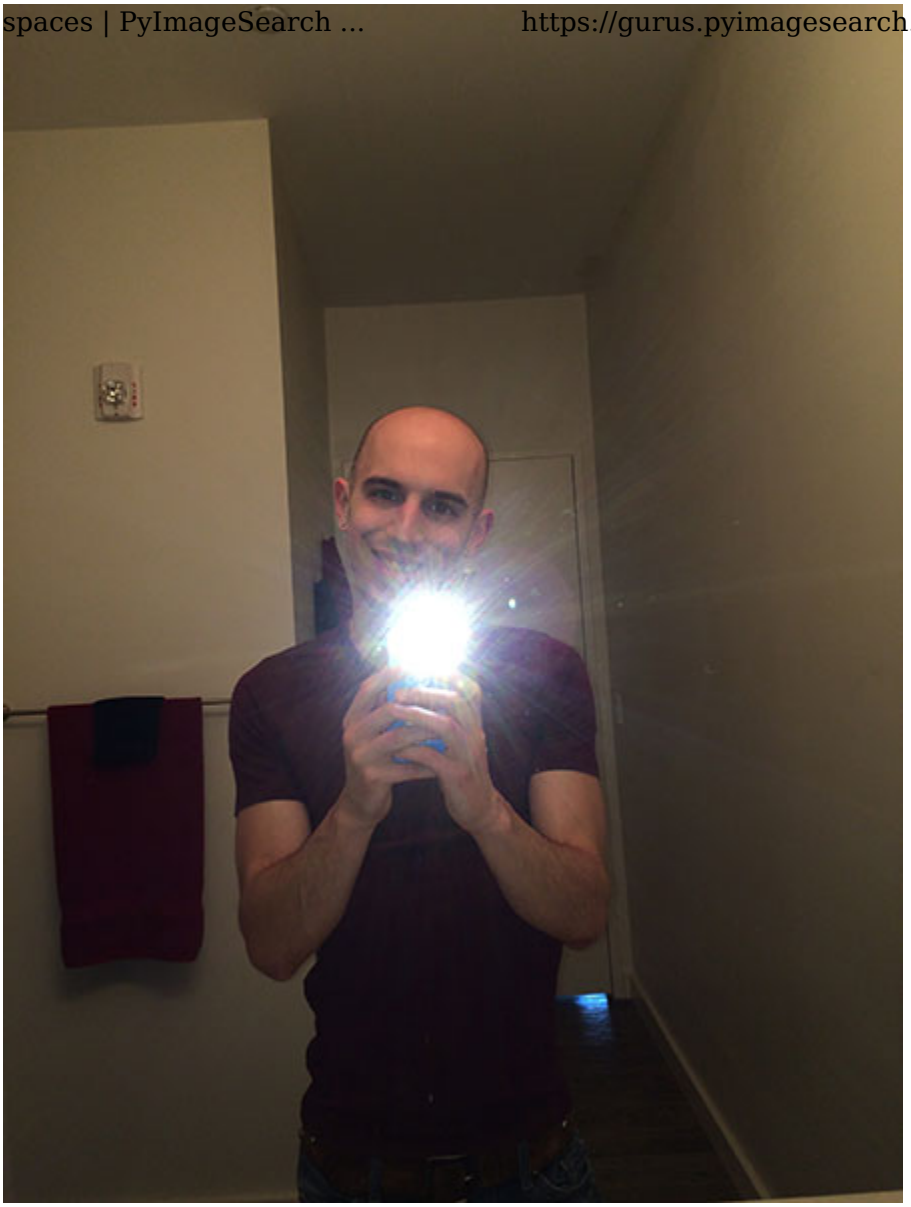


(https://gurus.pyimagesearch.com/wp-content/uploads/2015/03/color_spaces_lighting.jpg)

FIGURE 1: A CAMERA DOESN'T "FILM" AN OBJECT ITSELF — INSTEAD, IT CAPTURES THE LIGHT *REFLECTED OFF* THE OBJECT. IMAGE *SOURCE:* PRACTICAL COMPUTER VISION WITH SIMPLECV, 2012

The camera is not actually "filming" the object itself. Instead, it is capturing the light reflected from our object. This also implies that different objects in images will require different lighting conditions to obtain "good" results (where "good" is defined in terms of whatever the end goal of your algorithm is).

For instance, I thought I looked particularly good this morning so I captured a selfie of myself in my bathroom mirror:



(https://gurus.pyimagesearch.com/wp-content/uploads/2015/03/color_spaces_flash_selfie.jpg)

FIGURE 2: A MIRROR IS *REFLECTIVE SURFACE*, WHICH REFLECTS THE LIGHT BACK INTO THE CAMERA, CAUSING UNWANTED LIGHTING EFFECTS.

But whoops — I left the flash on my camera on! The mirror is *reflective* surface, thus the light is just going to bounce right off the surface and into my camera sensor. The photograph is quite poor and it would be near impossible to write code to detect my face in this image due to how much the flash is interfering with the lower part of my face.

Instead, when I turn my flash off and use the soft light from above which is not aimed at a reflective surface, I get my intended results:

(https://gurus.pyimagesearch.com/wp-content/uploads/2015/03/color_spaces_normal_selfie.jpg)

FIGURE 3: TURNING OFF THE FLASH AND USING OVERHEAD LIGHT YIELDS BETTER RESULTS.

Here, my face is clearly visible and it would be almost trivial to detect.

Again, you simply cannot compensate for poor lighting conditions. When developing an application to detect faces in images, which type of image would you prefer? The one in **Figure 2** when my face is practically not visible at all due to the flash? Or the image in **Figure 3** where my face is clearly visible and identifiable?

Obviously **Figure 3** is the preferred choice — and also a great example of why you need to consider your lighting conditions when developing a computer vision application.

Ingeneral, your lighting conditions should have three primary goals. Let's review them below:

High Contrast

Maximize the contrast between the Regions of Interest in your image (i.e. the "objects" you want to detect, extract, describe classify, manipulate, etc. should have sufficiently high contrast from the rest of the image so they are easily detectable).

Generalizable

Your lighting conditions should be consistent enough that they work well from one "object" to the next. If our goal is to identify various United States coins in an image, our lighting conditions should be generalizable enough to facilitate in the coin identification, whether we are examining a penny, nickel, dime, or quarter.

Stable

Having stable, consistent, and repeatable lighting conditions is the *holy grail* of computer vision application development. However, it's often hard (if not impossible) to guarantee — this is especially true if we are developing computer vision algorithms that are intended to work in outdoor lighting conditions. As the time of day changes, clouds roll in over the sun, and rain starts to pour, our lighting conditions will obviously change.

Even in my case with ID My Pill, having a *truly stable and repeatable* lighting condition cannot be done. Users from all around the world will capture pictures of medications under tremendously different lighting conditions (outside, inside, fluorescent light, quartz halogen, you name it) — and I simply have no control over it.

But let's say that ID My Pill was not developed for the consumer to validate their prescription pills. Instead, let's suppose that ID My Pill was used on the factory conveyor belt to ensure that each pill on the belt is of the same medication and there is no "cross-contamination" or "leakage" of different types of medication in the same production environment.

In the pill factory scenario, I'm *much more likely* to obtain stable lighting conditions. This is because I can:

1. Place the camera to capture photos of the pill wherever I want.
2. Have full control over the lighting environment — I can increase the lights, decrease them, or set up a pill "photo booth" that is entirely self-contained and apart from any other lighting source that could contaminate the identification.

As you can see, unstable lighting conditions are often harsh or impossible to guarantee. But it's *extremely important* that you at least consider the stability of your lighting conditions before you even write a single line of code.

So here's my key takeaway:

Strive *as much as possible* to obtain your ideal lighting conditions before you even write a single line of code. It's substantially more beneficial (and easier) to control (or at least acknowledge) your lighting conditions than it is to write code to compensate for inferior lighting.

Color Spaces

The second topic we are going to discuss in this lesson is *color spaces* and *color models*.

Simply put, a *color space* is just a specific organization of colors that allow us to consistently represent and reproduce colors.

For example, imagine browsing your local home improvement warehouse for your desired shade of paint for your living room. These color swatches at your home improvement store are likely organized in some coherent manner based on the color and tone of the swatch. Obviously this is quite the simplistic example and color spaces can be more rigorous and structured mathematically.

A *color model*, on the other hand, is an abstract method of numerically representing colors in the *color space*. As we know, RGB pixels are represented as a 3-integer tuple of a Red, Green, and Blue value.

As a whole, a *color space* defines both the *color model* and the abstract *mapping function* used to define actual colors. Selecting a color space also informally implies that we are selecting the color model.

The difference between the two is subtle, but important to cover as a matter of completeness.

In the rest of this section we'll be discussing the four main color spaces you'll come across when developing computer vision applications: *RGB*, *HSV*, *L*a*b**, and *grayscale* (which, again, is not technically a color space, but you'll be using it in nearly all computer vision applications you develop).

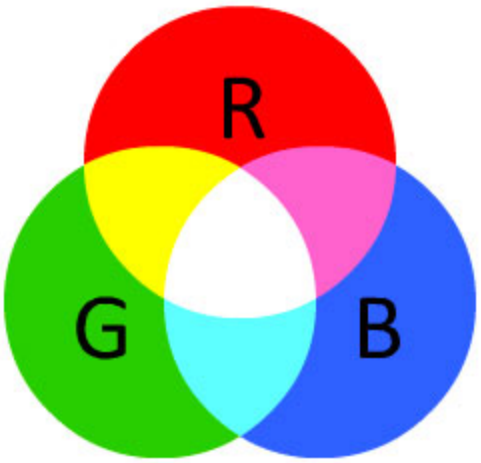
RGB

The first color space we are going to discuss is *RGB*, which stands for the Red, Green, and Blue components of an image. In all likelihood you are already very familiar with the RGB color space as we

I've used it many times already inside the PyImageSearch Gurus course.

To define a color in the RGB color model, all we need to do is define the amount of Red, Green, and Blue contained in a single pixel. Each Red, Green, and Blue channel can have values defined in the range *[0, 255]* (for a total of 256 "shades"), where *0* indicates no representation and *255* demonstrates full representation.

The RGB color space is an example of an *additive* color space: the more of each color is added, the brighter the pixel becomes and the closer it comes to white:



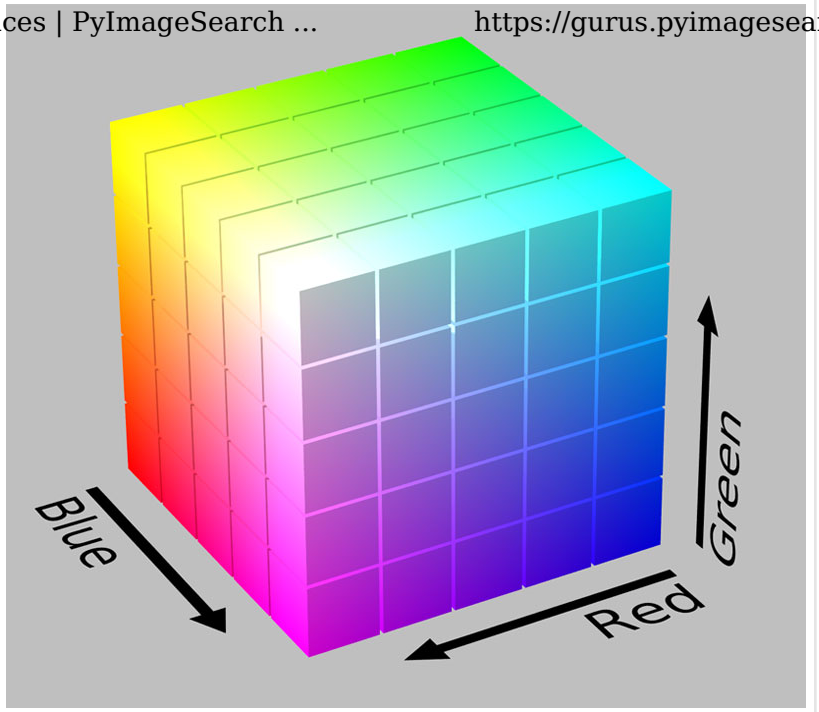
(https://gurus.pyimagesearch.com/wp-content/uploads/2015/03/color_spaces_rgb_additive.jpg)

FIGURE 4: THE RGB COLOR SPACE IS *ADDITIVE*. THE MORE RED, GREEN, AND BLUE YOU MIX TOGETHER, THE CLOSE YOU GET TO *WHITE*.

Feedback

As you can see, adding red and green leads to yellow. Adding red and blue yields pink. And adding all three red, green, and blue together we create white.

The *RGB* color space is commonly visualized as a cube:



(https://gurus.pyimagesearch.com/wp-content/uploads/2015/03/color_spaces_rgb_color_cube.jpg)

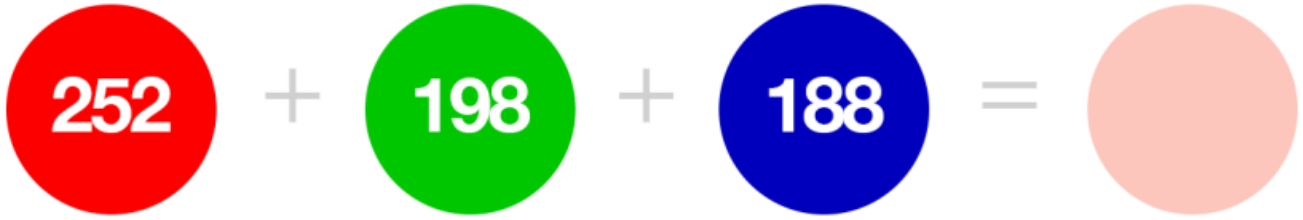
FIGURE 5: THE RGB COLOR CUBE, WHERE A DIMENSION IS GIVEN TO EACH OF THE RED, GREEN, AND BLUE COLORS.

Since an RGB color is defined as a 3-valued tuple, with each value in the range *[0, 255]*, we can thus think of the cube containing *256 x 256 x 256 = 16,777,216* possible colors, depending on how much Red, Green, and Blue we place into each bucket.

However, this is not exactly the most friendly color space for developing computer vision based applications. In fact, it's primary use is to display colors on a monitor.

Consider for instance if we want to determine how "much" red, green, and blue we need to create a single color.

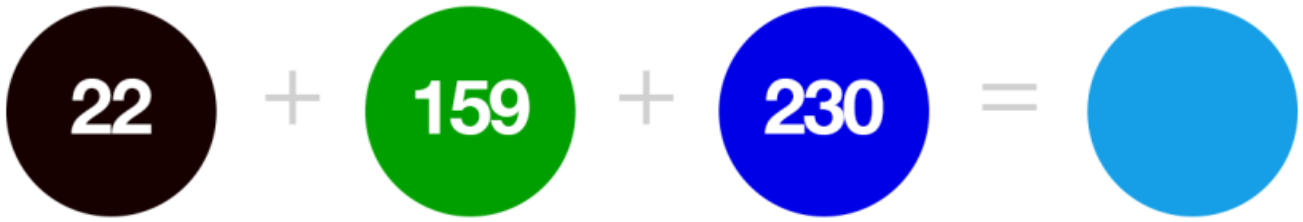
Would you imagine that it takes *R=252*, *G=198*, *B=188* to create my shade of skin in **Figure 3:**



(https://gurus.pyimagesearch.com/wp-content/uploads/2015/03/color_space_skin_example.png)

FIGURE 6: ADDING VARIOUS VALUES OF RED, GREEN, AND BLUE TO GET A "SKIN"-LIKE COLOR, LIKE IN THE PICTURE OF ME IN **FIGURE 3**.

Or what about this much *R=22*, *G=159*, *B=230* to get the shade of blue for the PyImageSearch logo:



(https://gurus.pyimagesearch.com/wp-content/uploads/2015/03/color_spaces_pyimagesearch_example.png)

FIGURE 7: CREATING THE SHADE OF BLUE FOR THE PYIMAGESEARCH LOGO. NOTICE HOW LITTLE "RED" GOES INTO THE ACTUAL OUTPUT COLOR.

Pretty unintuitive, right?

But despite how unintuitive the RGB color space may be, nearly all images you'll work with will be represented (at least initially) in the RGB color space.

Feedback

That all said, let's take a look at some code to display each channel of a RGB image:

color_spaces.py Python

```
# import the necessary packages
import argparse
import cv2

# construct the argument parser and parse the arguments
ap = argparse.ArgumentParser()
ap.add_argument("-i", "--image", required=True, help="Path to the image")
args = vars(ap.parse_args())

# load the original image and display it (RGB)
image = cv2.imread(args["image"])
cv2.imshow("RGB", image)

# loop over each of the individual channels and display them
for (name, chan) in zip(("B", "G", "R"), cv2.split(image)):
    cv2.imshow(name, chan)

# wait for a keypress, then close all open windows
cv2.waitKey(0)
cv2.destroyAllWindows()
```

Once again, we'll start off our example by importing the necessary packages, parsing command line

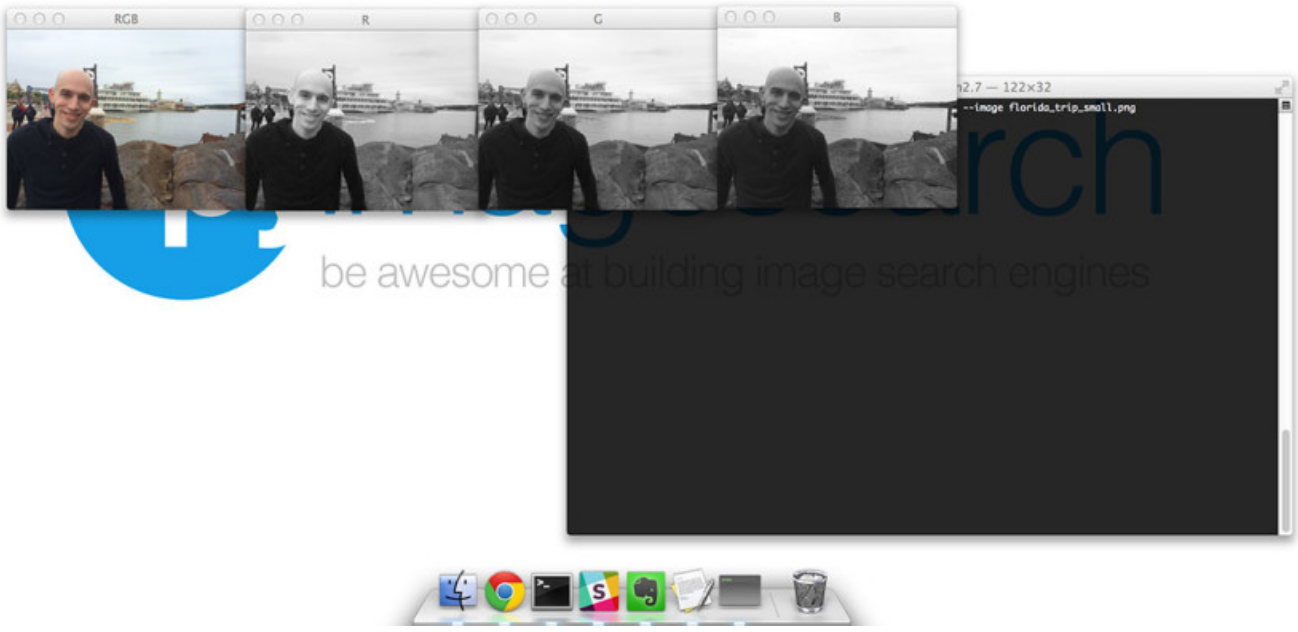
arguments, and loading our image from disk, which we display to our screen on **Line 12**.

We then loop over each of the image channels in Blue, Green, Red order since OpenCV represents images as NumPy arrays in reverse order on **Line 15**. For each of these channels we display them to our screen on **Line 16**.

To execute our script, just open up a terminal and execute the following command:

```
color_spaces.py                                                    Python
1 $ python color_spaces.py --image florida_trip_small.png
```

And here's our output image:



(https://gurus.pyimagesearch.com/wp-content/uploads/2015/03/color_spaces_rgb.jpg)

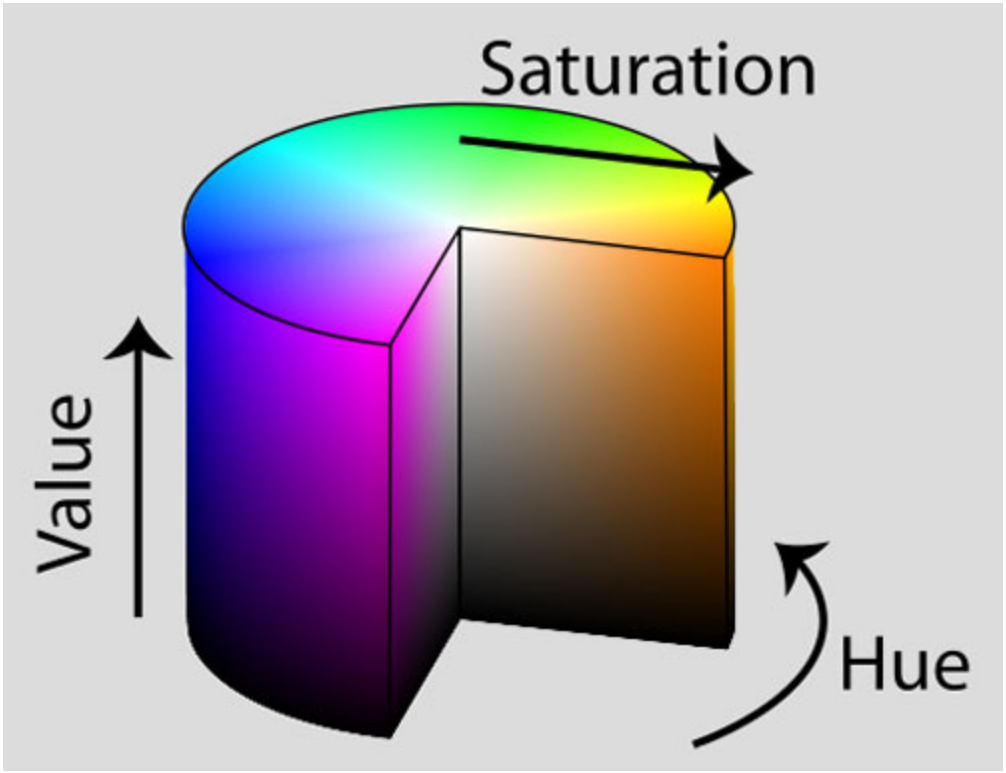
FIGURE 8: OUR ORIGINAL IMAGE IN THE RGB COLOR SPACE, FOLLOWED BY EACH OF THE INDIVIDUAL RED, GREEN, AND BLUE CHANNELS.

On the *left* we have our original RGB image, which consists of each of the Red, Green, and Blue channels added together.

So while the RGB is *the most used* color space, it's the not most *intuitive* color space either. Let's take a look at the *HSV* color space, which is a little more intuitive and easier to understand when defining color

HSV

The *HSV* color space transforms the *RGB* color space, remodeling it as a *cylinder* rather than a *cube*:



(https://gurus.pyimagesearch.com/wp-content/uploads/2015/03/color_spaces_hsv_color_cylinder.jpg)

FIGURE 9: REPRESENTING COLOR AS CYLINDER RATHER THAN A CUBE. A DIMENSION IN THE CYLINDER IS GIVEN TO HUE, SATURATION, AND VALUE, RESPECTIVELY.

As we saw in the *RGB* section, the "white" or "lightness" of a color is an additive combination of each Red, Green, and Blue component. But now in the HSV color space, the lightness is given its own separate dimension.

Let's define what each of the HSV components are:

- **Hue:** Which "pure" color we are examining. For example, all shadows and tones of the color "red" will have the same Hue.
- **Saturation:** How "white" the color is. A *fully saturated* color would be "pure," as in "pure red." And a color with zero saturation would be pure white.
- **Value:** The Value allows us to control the lightness of our color. A Value of zero would indicate pure black, whereas increasing the value would produce lighter colors.

important to note that different computer vision libraries will use different ranges to represent each of the Hue, Saturation, and Value components.

However, in the case of OpenCV, images are represented as 8-bit unsigned integer arrays. Thus, the Hue value is defined the range *[0, 179]* (for a total of 180 possible values, since *[0, 359]* is not possible for an 8-bit unsigned array) — the Hue is actually a *degree* (θ) on the HSV color cylinder. And both saturation and value are defined on the range *[0, 255]*.

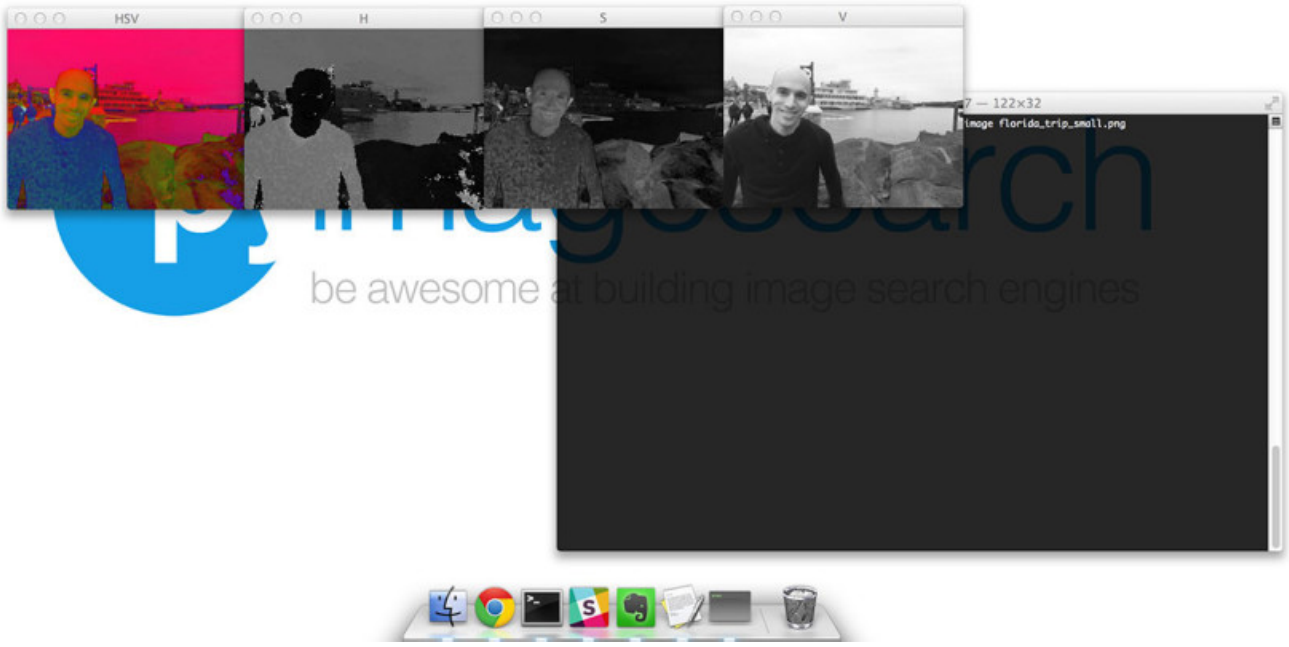
Let's look at some example code to convert an image from the RGB (or rather, BGR) color space to HSV:

color_spaces.py Python

```
22 # convert the image to the HSV color space and show it
23 hsv = cv2.cvtColor(image, cv2.COLOR_BGR2HSV)
24 cv2.imshow("HSV", hsv)
25
26 # loop over each of the individual channels and display them
27 for (name, chan) in zip(("H", "S", "V"), cv2.split(hsv)):
28     cv2.imshow(name, chan)
29
30 # wait for a keypress, then close all open windows
31 cv2.waitKey(0)
32 cv2.destroyAllWindows()
```

To convert our image to the HSV color space, we make a call to the `cv2.cvtColor` function. This function accepts two arguments: the actual `image` that we want the convert, followed by the output color space. Since OpenCV represents our image in BGR order rather than RGB, we specify the `cv2.COLOR_BGR2HSV` flag to indicate that we want to convert from BGR to HSV.

From there we'll go ahead and loop over each of the individual Hue, Saturation, and Value channels and display them to our screen:



(https://gurus.pyimagesearch.com/wp-content/uploads/2015/03/color_spaces_hsv.jpg)

FIGURE 10: VISUALIZING THE HSV COLOR SPACE.

Feedback

Notice how the *Value* component on the far right is essentially a grayscale image — this is because the value controls the actual *lightness* of our color, while both *Hue* and *Saturation* define the actual *color* and *shade*.

The HSV color space is used heavily in computer vision applications — especially if we are interested in tracking the color of some object in an image. It's far, far easier to define a valid color range using HSV than it is RGB.

L*a*b*

The last color space we are going to discuss is *L*a*b**.

While the *RGB* color space is easy to understand (especially when you're first getting started in computer vision), it's non-intuitive when defining exact shades of a color or specifying a particular *range* of colors.

On the other hand, the *HSV* color space is more intuitive but does not do the best job in representing how humans see and interpret colors in images.

For example, let's compute the Euclidean distance between the colors red and green, red and purple; and red and navy in the RGB color space:

Computing the Euclidean distance between colors — Python

```
>>> import math
>>> red_green = math.sqrt(((255 - 0) ** 2) + ((0 - 255) ** 2) + ((0 - 0) ** 2))
>>> red_purple = math.sqrt(((255 - 128) ** 2) + ((0 - 0) ** 2) + ((0 - 128) ** 2))
>>> red_navy = math.sqrt(((255 - 0) ** 2) + ((0 - 0) ** 2) + ((0 - 128) ** 2))
>>> red_green, red_purple, red_navy
(360.62445840513925, 180.31361568112376, 285.3226244096321)
```

So that begs the question: what do these distance values *actually represent?*

Is the color red *somehow* more perceptually similar to purple rather than green?

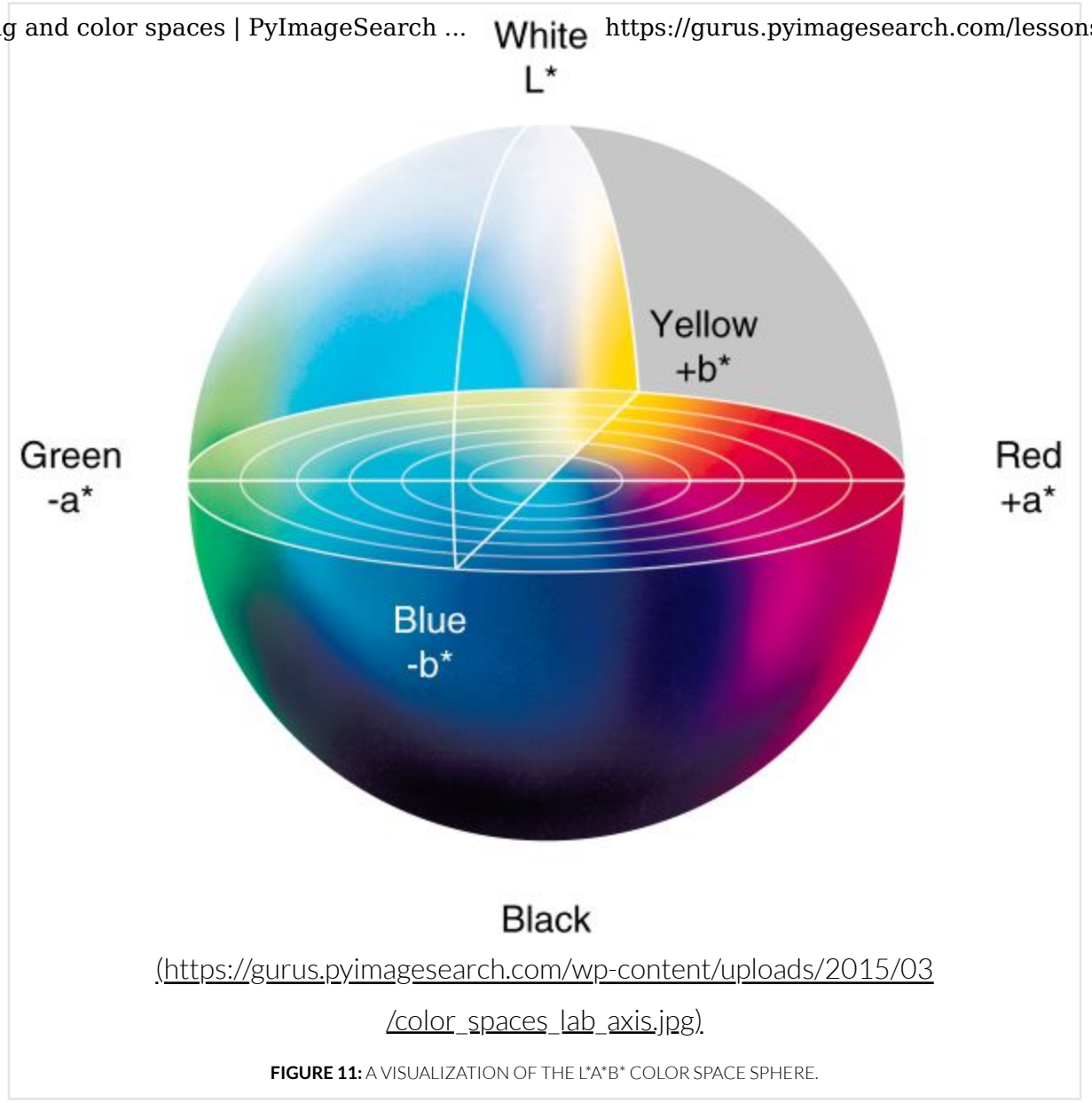
The answer is a simple *no* — even though we have defined our color spaces on objects like a cube and a cylinder, these distances are actually quite arbitrary and there is actual no way to "measure" the perceptual difference in color between various colors in the RGB and HSV color spaces.

That is where the L*a*b* color space comes in — its goal is to mimic the methodology in which humans see and interpret color.

This means that the Euclidean distance between two arbitrary colors in the L*a*b* color space has actual *perceptual meaning*.

The addition of perceptual meaning makes the L*a*b* color space less intuitive and understanding as RGB and HSV, but it is heavily used in computer vision.

Essentially, the L*a*b* color space is a 3-axis system:



(https://gurus.pyimagesearch.com/wp-content/uploads/2015/03/color_spaces_lab_axis.jpg)

FIGURE 11: A VISUALIZATION OF THE L*A*B* COLOR SPACE SPHERE.

Where we define each channel below:

- **L-channel:** The "lightness" of the pixel. This value goes up and down the vertical axis, white to black, with neutral grays at the center of the axis.
- **a-channel:** Originates from the center of the L-channel and defines pure green on one end of the spectrum and pure red on the other.
- **b-channel:** Also originates from the center of the L-channel, but is perpendicular to the a-channel. The b-channel defines pure blue at one of the spectrum and pure yellow at the other.

Again, while the L*a*b* color space is less intuitive and not as easy to understand as the HSV and RGB color spaces, it is *heavily* used in computer vision. This is due to the distance between colors having an actual perceptual meaning, allowing us to overcome various lighting condition problems. It also serves as a powerful color image descriptor.

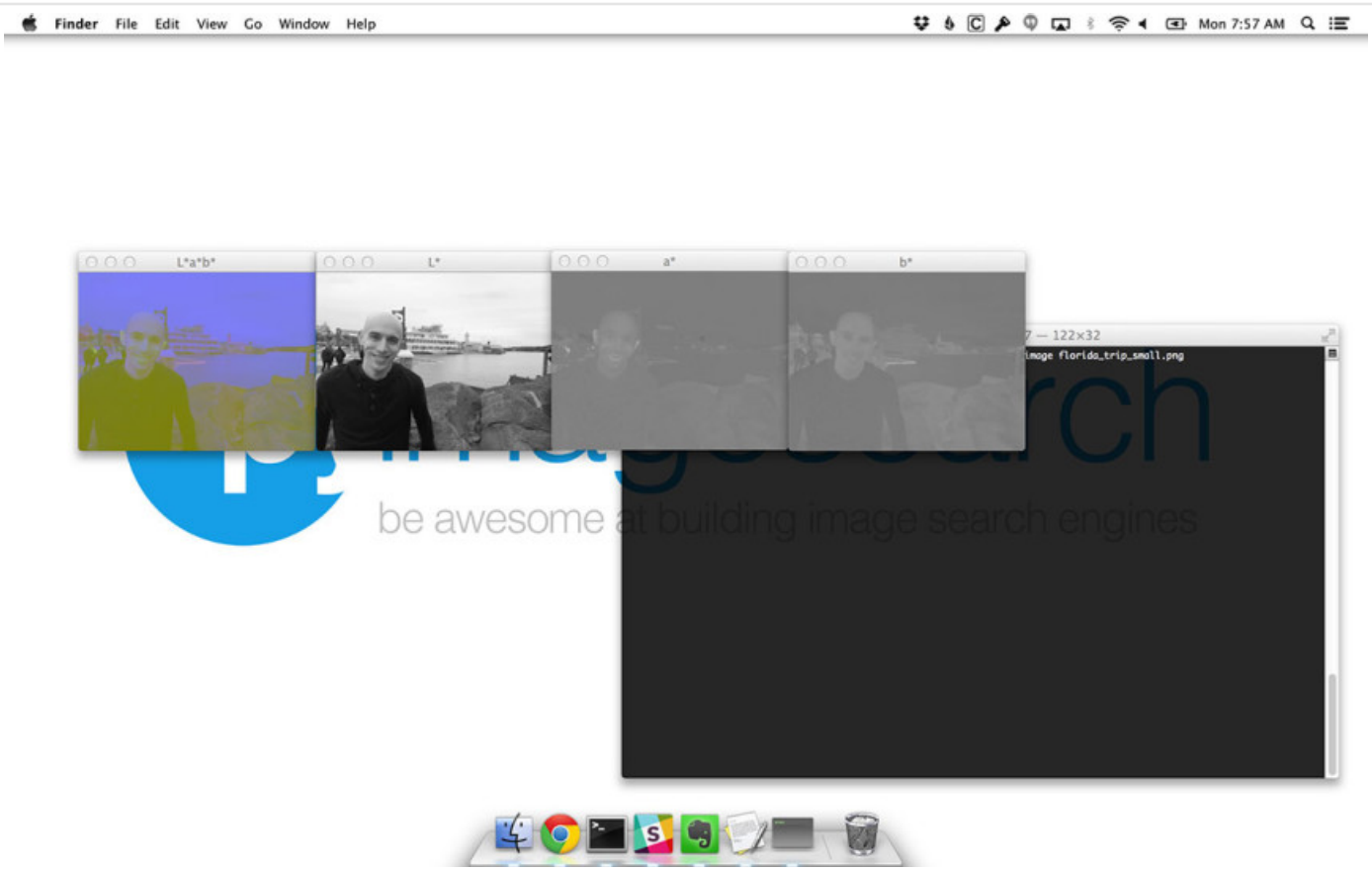
Now, let's look at how we can convert our images to the L*a*b* color space:

color_spaces.py Python

```
34 # convert the image to the L*a*b* color space and show it
35 lab = cv2.cvtColor(image, cv2.COLOR_BGR2LAB)
36 cv2.imshow("L*a*b*", lab)
37
38 # loop over each of the individual channels and display them
39 for (name, chan) in zip(("L*", "a*", "b*"), cv2.split(lab)):
40     cv2.imshow(name, chan)
41
42 # wait for a keypress, then close all open windows
43 cv2.waitKey(0)
44 cv2.destroyAllWindows()
```

The conversion to the L*a*b* color space is once again handled by the `cv2.cvtColor` function — but this time we provide the `cv2.COLOR_BGR2LAB` flag to indicate that we want to convert from the BGR to L*a*b* color space.

From there, we loop over each of the L*, a*, and b* channels, respectively, and display them to our screen:



(https://gurus.pyimagesearch.com/wp-content/uploads/2015/03/color_spaces_lab.jpg)

FIGURE 12: VISUALIZING EACH OF THE L*, A*, AND B* CHANNELS OF AN IMAGE.

Similar to our HSV example, we have the L*-channel which is dedicated to displaying how *light* a given pixel is. The a* and b* then determine the shade and color of the pixel.

Grayscale

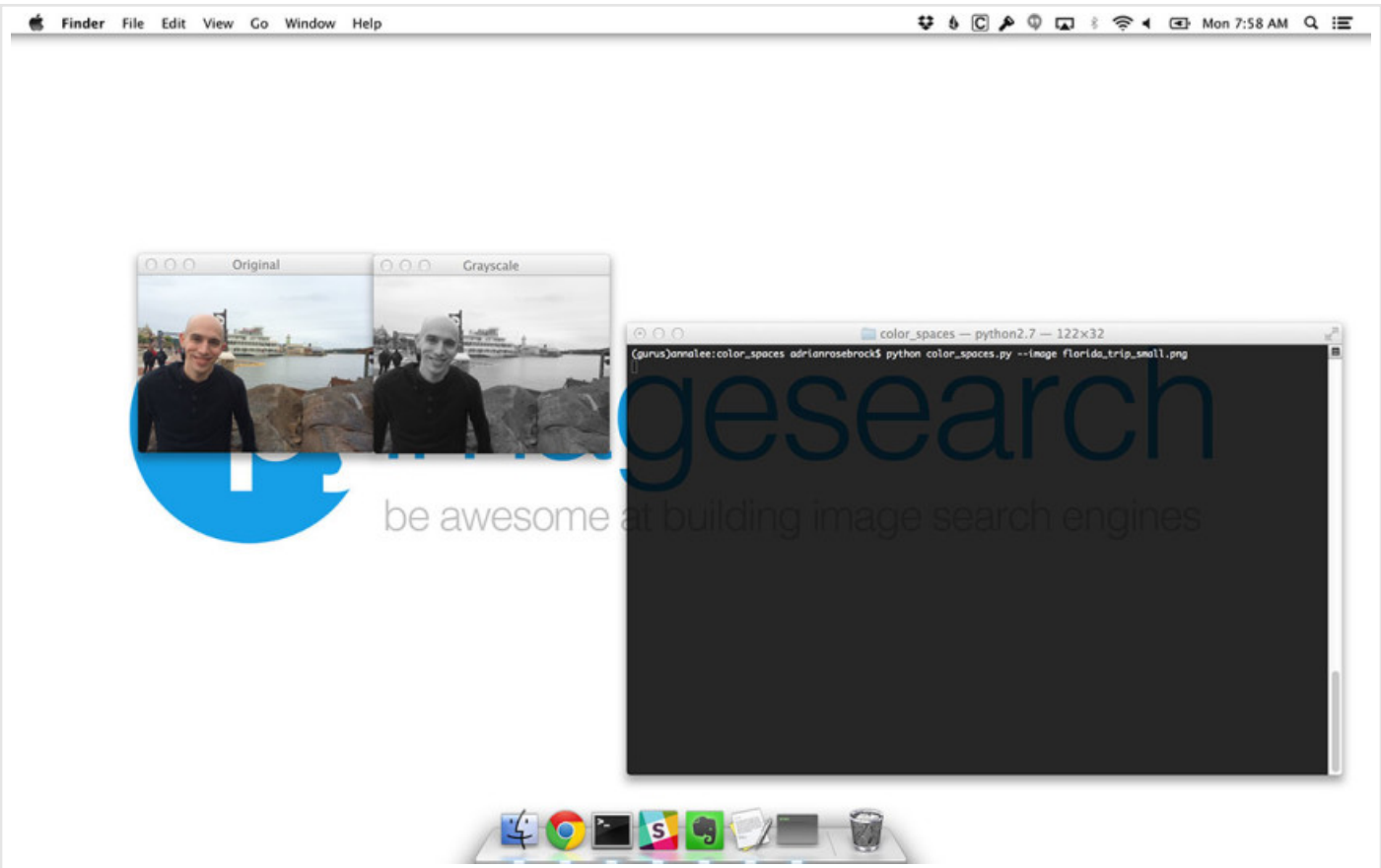
The last color space we are going to discuss isn't actually a color space — it's simply the grayscale representation of a RGB image.

A grayscale representation of an image throws away the color information of an image and can also be done using the `cv2.cvtColor` function:

color_spaces.py Python

```
46 # show the original and grayscale versions of the image
47 gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
48 cv2.imshow("Original", image)
49 cv2.imshow("Grayscale", gray)
50 cv2.waitKey(0)
```

Where our output is a grayscale image:



(https://gurus.pyimagesearch.com/wp-content/uploads/2015/03/color_spaces_grayscale.jpg)

FIGURE 13: CONVERTING OUR IMAGE TO GRAYSCALE.

The grayscale representation of an image is often referred to as "black and white," but this is not technically correct. Grayscale images are single channel images with pixel values in the range *[0, 255]* (i.e. 256 unique values).

Feedback

Quite literally, images are called *binary* images and thus only have two possible values: *0* ***or*** *255* (i.e. only 2 unique values).

Be careful when referring to grayscale image as black and white to avoid this ambiguity.

However, converting an RGB image to grayscale is not as straightforward as you may think. Biologically, our eyes are more sensitive and thus perceive more green and red than blue.

Thus when converting to grayscale, each RGB channel is ***not*** weighted uniformly, like this:

$$Y = 0.333 \times R + 0.333 \times G + 0.333 \times B$$

Instead, we weight each channel differently to account for how much color we perceive of each:

$$Y = 0.299 \times R + 0.587 \times G + 0.114 \times B$$

Again, due to the cones and receptors in our eyes, we are able to perceive nearly 2x the amount of green than red. And similarly, we notice over twice the amount of red than blue. Thus, we make sure to account for this when converting from RGB to grayscale.

The grayscale representation of an image is often used when we have no use for color (such in detecting faces or building object classifiers where the color of the object does not matter). Discarding color thus allows us to save memory and be more computationally efficient.

Feedback

Summary

In this lesson we learned about lighting conditions and the critical role they play in computer vision applications. The key takeaway is to ***always consider your lighting conditions before you write a single line of code!***

And in situations where you can actually *control* your lighting conditions, you are even better off. In general, you'll find that it's easier to control your lighting conditions than to write code that compensates for images captured under poor quality.

Second, we reviewed three very common color spaces in computer vision: *RGB*, *HSV*, and *L*a*b**.

The RGB color space is the most common color space in computer vision. It's an *additive* color space, where colors are defined based on combining values of red, green, and blue. While quite simple, the RGB color space is unfortunately unintuitive for defining colors as it's hard to pinpoint *exactly* how much red,

green, and blue compose a certain color. Imagine looking at a specific region of an image and trying to identify how much red, green, and blue there is using only your naked eye!

Luckily, we have the HSV color space to compensate for this problem. The HSV color space is also intuitive, as it allows us to define colors along a *cylinder* rather than a RGB *cube*. The HSV color space also gives lightness/whiteness its own separate dimension, making it easier to define shades of color.

However, both the RGB and HSV color spaces fail to mimic the way humans perceive color — there is no way to mathematically *define* how *perceptually different* two arbitrary colors are using the RGB and HSV models. And that's exactly why the L*a*b* color space was developed. While more complicated, the L*a*b* provides with *perceptual uniformity*, meaning that the distance between two arbitrary colors has actual *meaning*.

All that said, you'll find that you will use the RGB color space for most computer vision applications. While it has many shortcomings, you cannot beat its simplicity — it's simply adequate enough for most systems.

There will also be times when you use the HSV color space — particularly if you are interested in tracking an object in an image based on its *color*. It's very easy to define color ranges using HSV.

For basic image processing and computer vision you likely won't be using the L*a*b* color space that often. But when you're concerned with color management, color transfer, or color consistency across multiple devices, the L*a*b* color space will be your best friend. It also makes for an excellent color image descriptor.

Finally, we discussed converting an image from RGB to grayscale. While the grayscale representation of an image is not technically a color space, it's worth mentioning in the same vein as RGB, HSV, and L*a*b*. We often use grayscale representations of an image when color is not important — this allows us to conserve memory and be more computationally efficient.

Downloads:

Download the Code (https://gurus.pyimagesearch.com/protected/code/computer_vision_basics/color_spaces.zip)

	Quizzes	Status
1	Lighting and Color Spaces Quiz (https://gurus.pyimagesearch.com/quizzes/lighting-and-color-spaces-quiz/)	

← Previous Lesson (https://gurus.pyimagesearch.com/lessons/smoothing-and-blurring/) Next Lesson → (https://gurus.pyimagesearch.com/lessons/thresholding/)

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Feedback

Resources & Links

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- PyImageSearch Virtual Machine (https://gurus.pyimagesearch.com/pyimagesearch-virtual-machine/)
- Setting up your own Python + OpenCV environment (https://gurus.pyimagesearch.com/setting-up-your-python-opencv-development-environment/)
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