Computer Vision 1
Assignment 1

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1 Photometric Stereo

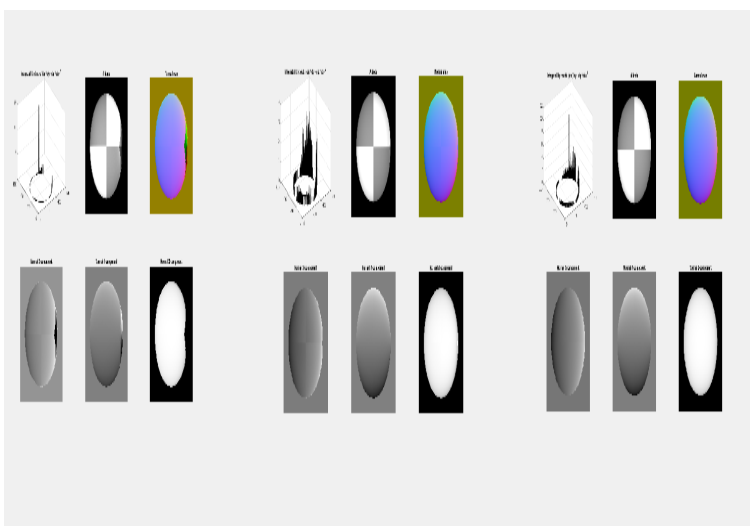
Estimating Albedo and Surface Normal

Question - 1

We expected to find true color with no shadows and shadows seem to still be there at the edge of the ball.

We have found that 20 images is the minimum number of images to obtain a full estimation. Our strategy was to start with multiple of 5's and then once we started obtaining complete images, increment by 1 in order to see the treshold value.

There trick is the following. If there really is no ambient illumination, then we can form a matrix from the image vector and multiply both sides by this matrix. We do this in order to zero out any equations from points that are in shadow. This trick is not needed when we have 25 images but is needed for 5 images.



Results for10, 15 and respectively 20 images

Question - 2

The errors are relatively small everywhere (coming from numeric errors of approximation) except for a couple of pixels from the eye, where the approximated derivative between two pixels can vary a lot and thus produce a big error. Also the errors are smaller when using 25 images instead of 5 as can be seen in the following figure:

31st Conference on Neural Information Processing Systems (NIPS 2017), Long Beach, CA, USA.

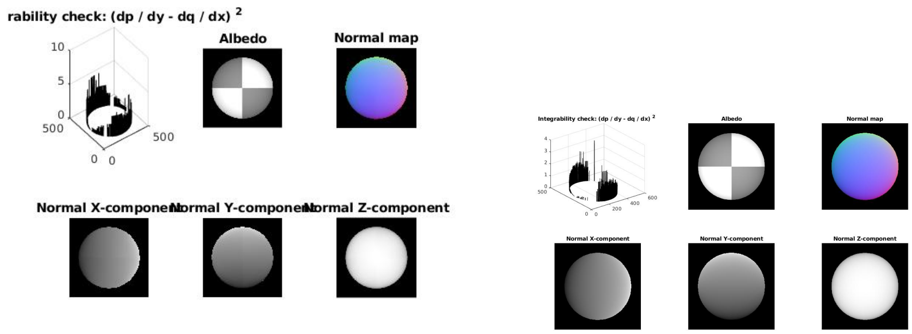


Figure. The Components and integrability check using 5 images (left) and 25 images(right).

Question - 3

Depending on which method we use, the column/row peaks and error propagates on rows/columns. When taking the average, due to the high peaks, it seems to find more peaks on both axes and perform worse. The values in themselfs might be better:

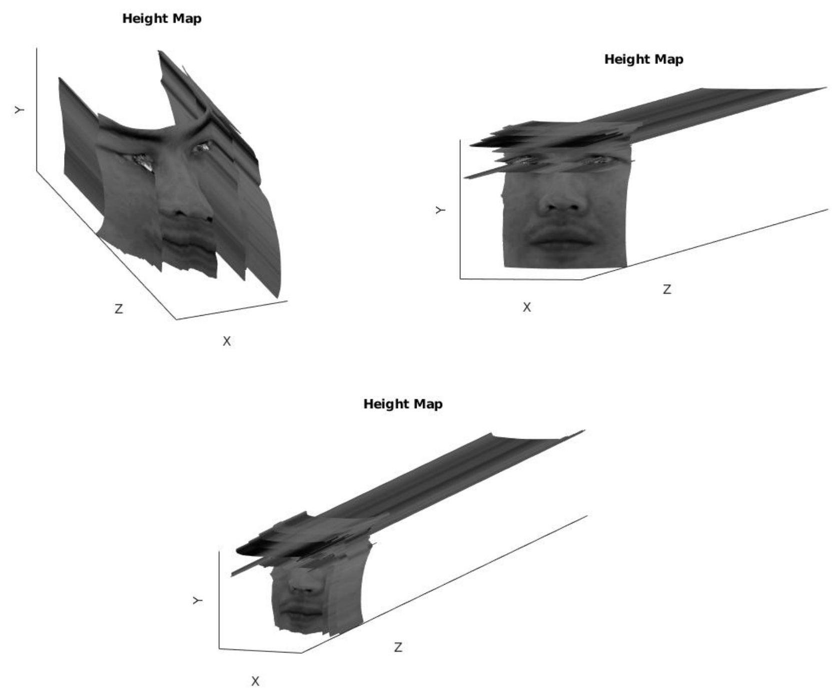
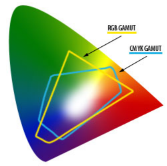


Figure. row (left up), column (right up), average (down)

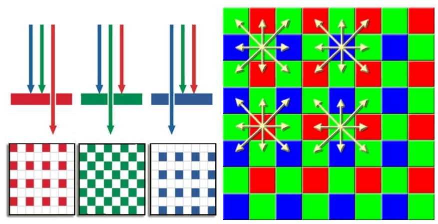
2 Color Spaces

RGB Color Model

Most consumer cameras are RGB because this additive color model can provide most of the colors that the human eye can see. We are satisfied with them because the colors that it cannot reproduce are rarer than the ones it can reproduce.

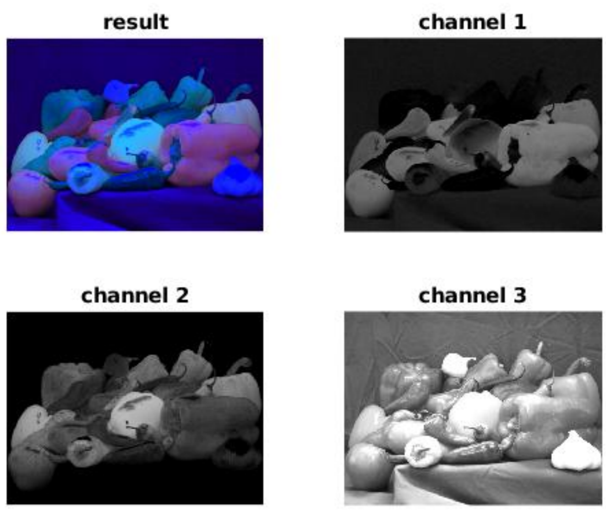


To create an RGB image, filters are placed over pixels and then the actual value of a pixel is interpolated with adjacent pixels.

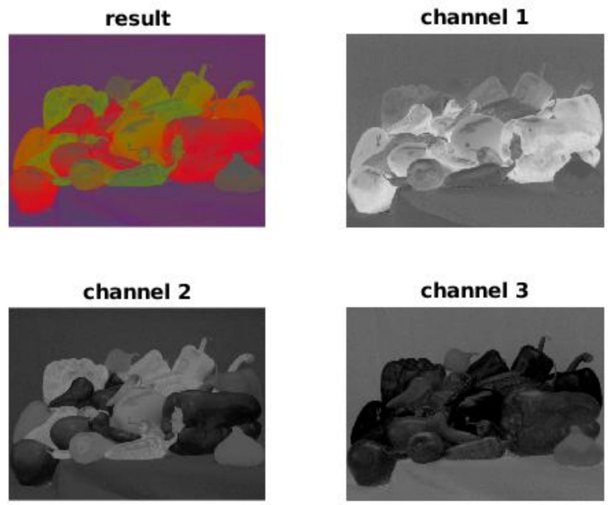


Color Space Properties

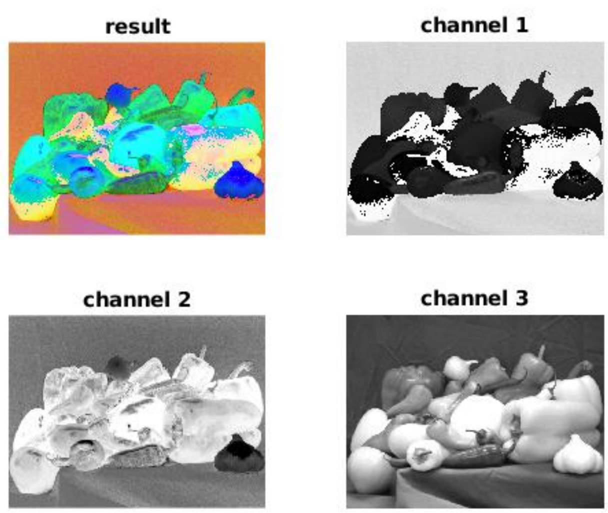
- Opponent color space



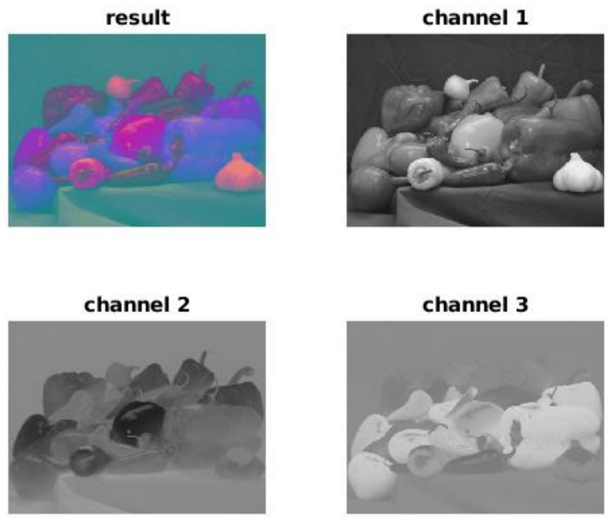
- Normalized rgb color space
  The normalized rgb model used for shadow detection.



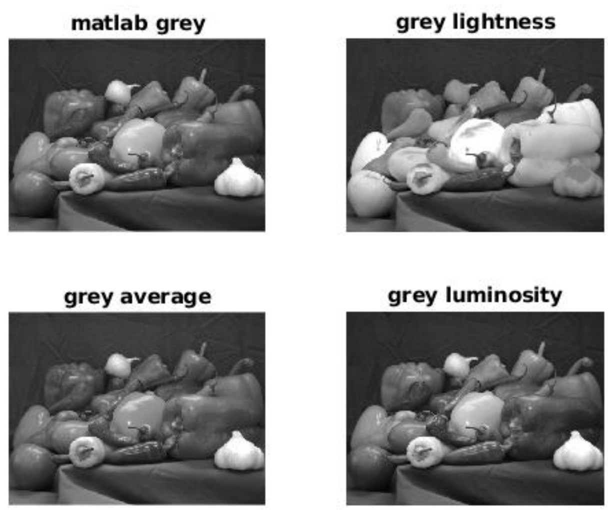
- HSV color space The HSV model and each channel have many applications. For example, the Hue is invariant to lighting (less variant) and it is used together with other models to detect TODO complete here with what those points of maximum light were called



- YCbCr color space
  YCbCr, used widely in video and image compression schemes.



- Gray-matlab-lightness-average-luminosity color space
  Each greyscale method does some type of averaging: lightness reduces contrast, average averages across all channels, luminosity applies a weighted average that is closer to the human eye due to the weight of the green channel. The matlab version of rgb2grey outputs a greyscale image where the saturation and hue are removed.



More on Color Spaces

CMYK is another type of color model that is heavily used in printing. This is the case because it is a subtractive model (by contrast RGB is additive) and paper does not produce light (by contrast RGB is used on digital devices that produce light).

3 Intrinsic Image Decomposition

The observed color at any point of an object is influenced by many factors, including the shape and material of the object, the position and colors of the light sources, and the position of the viewer.

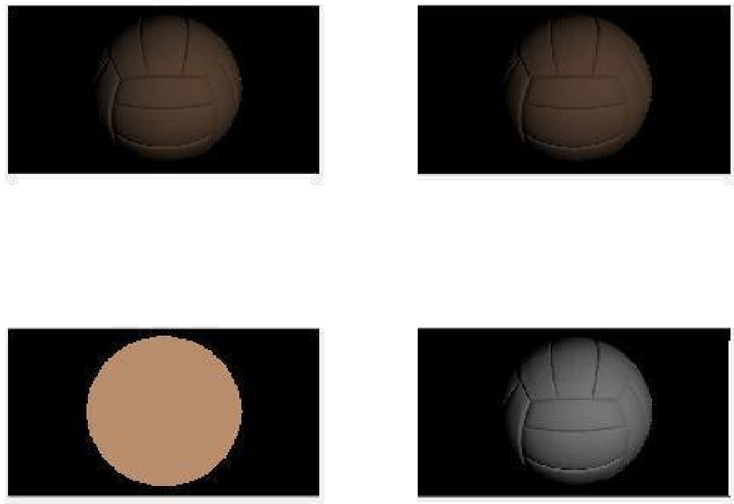


Figure 1: IID ball reconstruction

In an intrinsic image decomposition, intrinsic images of a given scene are the images depicting a single physical characteristic of the scene. Examples of such characteristics are: reflectance, shading, orientation, distance, transparency, specularity, illumination and so on.

The specular component accounts for highlights that are due to viewpoint, geometry and illumination. Decomposing an image into shading, reflectance and specularity ca be advantageous for certain computer vision algorithms such as image segmentation.

Moreover, [1] presents a spectral intrinsic image decomposition model (SIID), which is dedicated to resolve a natural scene into its purely independent intrinsic components: illumination, shading and reflectance. By introducing spectral information, our work can solve many challenging cases such as material classification and recognition, shape-from-shading and spectral image relighting.

Almost all the intrinsic image decomposition from literature are composed of synthetic images because it is very difficult and time consuming to construct such large-scale datasets from genuine images with different shading angles.

The original image can be reconstructed from its intrinsics, reflectance and shading. This can be visualize in figure [1]

Recoloring

The actual material can be obtained from the RGB of the reflectance.

The original ball and the recolored ball with pure green and respectively magenta can be visualized in figure [2].

The color distribution over the object does not appear to be uniform due to the fact that the ball shading is also not uniform.

4 Color consistency

In the gray world assumption, we assume that the color in each sensor channel (R,G,B) averages to gray over the entire image. This is one of the most common assumption made when trying to estimate the spectral distribution of the illuminant. Each sensor channel is averaged independently.

Problem arise with this assumption when the objects in the image don't average to gray. An image in which many similar colors are presen t gives a bad result where the dominant color is illuminated because the algorithm needs a wide range of colors.

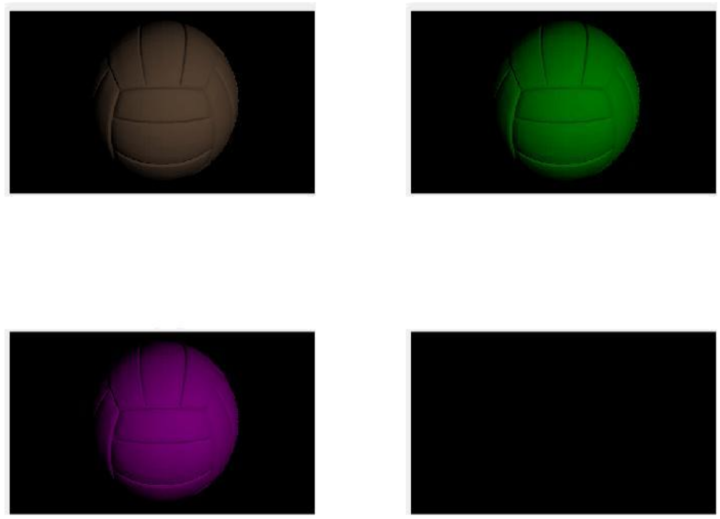


Figure 2: Recoloring of ball

Figure 3: Gray world algorithm applied to awb.jpg

Other algorithms

General transformation based approaches

The sensor used to capture the color image is calibrated and its response is studied under different illumination conditions. To obtain an illuminant invariant description of an image captured under unknown illumination conditions, transformation based approaches were introduced. These approaches map the surface reflectance observed under the canonical illuminant to the surface reflectance of the scene observed under the unknown illuminant. They assume proper knowledge of the sensor characteristics and other assumptions such as uniform illumination and single illumination source.

The color constancy algorithms in [2,3] are based on diagonal matrix transformation. Color constancy is obtained by simply taking the dot product of the diagonal matrix and the image matrix obtained under unknown illumination, which is equivalent to independently scaling each channel by a factor.

Figure 4: Gray world algorithm applied to awb.jpg

Figure 5: Counter-example for the gray-world algorithm

Machine learning approaches

Machine learning algorithms are data based approaches. They involve two stages: training and testing. In the training stage, the algorithms learns the functional mapping between the input and the output data. Based on this learnt mapping, they predict the output of previously unseen data in the testing stage.

Initial learning approaches to color constancy were based on neural networks. Cardei et al. [4] proposed a multilayer perceptron (MLP) feedforward neural network based approach in the chromaticity spaces. They proposed a network architecture which consisted of 3600 input nodes, 400 neurons in the first hidden layer, 40 neurons in the second hidden layer and 2 output neurons. A significantly large amount of images were needed in order to train the network. They showed that neural networks achieved better color constancy than color by correlation. Stanikunas et al. [5] performed an investigation of color constancy using neural network and compared it to the human vision system. They concluded that background color information is important to achieve human equivalent color constancy in machine vision systems.

References

[1] Xi Chen, Weixin Zhu, Yang Zhao, Yao Yu, Yu Zhou, Tao Yue, Sidan Du, and Xun Cao, "Intrinsic decomposition from a single spectral image," Appl. Opt. 56, 5676-5684 (2017)

[2] G. H. Finlayson, “Color in Perspective,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 18, no. 10, pp. 1034-1038, 1996

[3] G. D. Forsyth, “A Novel Algorithm for Color Constancy,” International Journal of Computer Vision, vol. 5, no.1, pp. 5-36, 1990.

[4] V. Cardei, B. V. Funt, and K. Barnard, “Estimating the Scene Illumination Chromaticity Using a Neural Network,” Journal of the Optical Society of America A, vol. 19, no. 12, pp. 2374-2386, 2002.

[5] R. Stanikunas, H. Vaitkevicius, and J. J. Kulikowski, “Investigation of Color constancy with a Neural Network,” Neural Networks, vol. 17, pp. 327-337, 2004.