

Photonics Laboratory Report: Spectral Imaging

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Abstract

This experiment aimed to explore the principles of spectral imaging, the acquisition process of spectral images, and the extraction of associated data. A Nuance multispectral imaging camera was used to take pictures of a painting, a white reference paper, a color checker palette, and a yellowish UEF metameric logo. These samples were placed under a GretagMacbeth Spectra light III daylight simulation light booth, and the camera took pictures of them at a perpendicular angle. MATLAB was used to evaluate the data, RGB images were created, and the reflectance spectra of each pixel in the images were computed and displayed.

Contents

1	The	ory	1
	1.1	Spectral Imaging	1
	1.2	RGB Image Formation	1
	1.3	Reflectance	2
	1.4	Metamerism	3
	1.5	The non-uniformity behavior of white reference image	4
	1.6	Measurement Task	4
	1.6.	1 Setup Configuration	4
	1.6.	2 Sample images.	5
2	Res	ults	5
	2.1	Reflectance Imaging at a Single Wavelength	5
	2.2	Construction of RGB Images Using Selected Wavelengths	6
	2.3	Reflectance Spectra Analysis Across Selected Image Points	6
	2.3.	1 White Reference Variability	7
	2.3.	2 Color checker	8
	2.3.	3 Painting	8
	2.3.	4 Metamerism Analysis	9
3	Con	clusion	0
R	eferenc	es	1
A	ppendi	x1	3

1 Theory

"To sample visual data at various wavelength bands, spectral imaging" [1] combines two fields of study: spectroscopy and photography. Hyperspectral (> 20 wavelength bands) and multispectral (< 20 wavelength bands sampled) spectrum imaging are the two general categories [1]. Maybe a more accurate description would be that hyperspectral imaging gathers enough information over a certain spectral range to rebuild a continuous spectrum, whereas multispectral imaging gathers information from several discrete but non-contiguous wavelengths [2].

In this section, we discuss the terminologies and concepts related to spectral imaging, RGB color formation, reflectance, and metamerism.

1.1 Spectral Imaging

Standard cameras function within the visible spectrum, capturing imagery across three primary wavelengths: red, green, and blue. By incorporating or overlaying these primary colors, they create the conventional RGB (Red, Green, and Blue) image, resulting in a diverse palette of colors for each pixel within the image [3]. Spectral imaging, however, includes a broad range of wavelengths, [4] integrating imaging technology with spectroscopy, resulting in three-dimensional data composed of multiple two-dimensional images captured at different wavelengths called a spectral image.

Spectral imaging can make use of x-rays, the visible, ultraviolet, and infrared spectrums, or a mixture of them known as multispectral imaging [2]. It could involve lighting from outside the visible range, simultaneously capturing "image data in visible and non-visible bands or using optical filters to capture a particular spectral range". For every pixel in an image, hundreds of wavelength bands can likewise be recorded. Widely utilized in biomedical fields, planetary studies, art preservation, and similar domains, spectral imaging technology is valued for producing exceptionally high-quality images [5].

1.2 RGB Image Formation

The RGB image is made up of only three channels or bands [6]—Red, Green, and Blue—it combines the three primary colors of light: red, green, and blue, in varying proportions. These

three colors are often referred to as additive colors because they are combined to form the complete image.

In MATLAB, "an RGB image, also referred to as a true color image, is stored as a data array with dimensions m-by-n-by-3. This array defines the red, green, and blue color components for each individual pixel" [7]. Each channel records the intensity of its corresponding color at that pixel, with intensities ranging from 0 to 255. For instance, if a pixel has a blue value of 255, a green value of 0, and a red value of 0, it will appear as a bright blue color.

RGB images can be created from spectral images, and the reverse is also possible. The image below illustrates the process of reconstructing spectral images and forming RGB images from hyperspectral images.

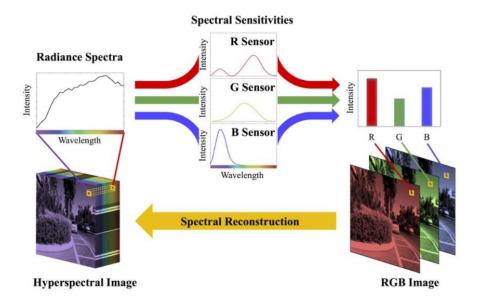


Figure 1: RGB image formation (Hyperspectral → RGB image) and spectral reconstruction (RGB → Hyperspectral image) [8]

1.3 Reflectance

Reflectance refers to "the ratio of reflected radiant flux (optical power) to the incident flux at a reflecting object, such as an optical component or system". It typically varies based on the direction of incident light and the optical frequency or wavelength [9]. Reflectance values range from 0 to 1, and a surface's reflectance is influenced by the wavelength of the incoming light. Reflectance provides insight into various surface characteristics, such as color and texture [10].

Spectral reflectance (ρ) represents the ratio of the radiant flux reflected (Φ_r) by an object to the radiant flux incident (Φ_i) upon it at a particular wavelength [11]. This mathematical expression is given by:

$$\rho(\lambda) = \frac{\Phi_r(\lambda)}{\Phi_i(\lambda)} \tag{I}$$

Reflectance is often categorized as either specular or diffuse. Specular reflectance involves the angle of reflection being equal and opposite to the angle of incidence. In contrast, for diffuse reflectance, radiant flux is reflected at all angles within the hemisphere bounded by the sample plane, except in the direction of the specular reflection angle [12]. Various materials possess distinct reflectance characteristics, which can be leveraged to identify and distinguish them through spectral imaging [13].

1.4 Metamerism

Metamerism is when lights look the same to the eye, or to the sensor system, even though they have different distributions of spectral radiant power across the visible spectrum – that is - it occurs when two colors appear identical under one lighting condition but different under another [14, 15, 16]. This phenomenon is influenced by both the light source and how the surface reflects it, thereby altering the perceived color of the surface. For instance, imagine a material illuminated by incandescent light in one scenario and daylight in another. Since incandescent light emits more energy in the red spectrum, the material may appear more reddish compared to under daylight, which has less red energy but peaks in the blue spectrum. When two samples have the same reflectance value at least across three wavelengths, they are termed metameric pairs [17, 18]. Metamerism can manifest in various forms:

- *Illuminant metamerism* occurs when two items match under one light source for one observer but not under another light source for the same observer [19].
- *Observer metamerism* arises from differences in color perception among observers and is subjective, though training and careful selection of colorists can mitigate risks [19].
- *Geometric metamerism* can be managed by evaluating samples at the same distance and angle relative to the light source (typically 45°) [19].

Metameric samples have differing spectral power distributions due to variances in the paints or dyes used to color the surface, as well as disparities in the illumination conditions under which they are observed.

1.5 The non-uniformity behavior of white reference image

The purpose of the white reference in spectral imaging is to calibrate the imaging system and ensure accurate color and reflectance measurements. It serves as a known reflectance standard to calibrate the system and is used for normalization of the captured data to correct for variations due to uneven lighting or sensor sensitivity. This ensures consistent and comparable spectral data across different samples and imaging sessions. It provides a baseline measurement against which all other reflectance values are compared, facilitating the identification and quantification of the samples' spectral characteristics [20].

1.6 Measurement Task

1.6.1 Setup Configuration

In this experiment, we used the Nuance Multispectral Imaging Camera System for obtaining spectral cubes and the Spectra Light III Color light box to uniformly illuminate our samples as shown in Fig. 2.





Figure 2: (a) Nuance Multispectral Imaging Camera System CRI Model N-MSI-EX and (b) SpectraLight III Color Viewing Booth

Following the instruction put forward on the lab manual, we calibrated the computer program (Nuance) to the given parameters including setting up the autoexposure. We used the whole wavelength range of 450-950 nm with 10 nm interval to obtain 26 .tif images per sample. We also manually adjust the tripod of the camera to have a perfect normal to the sample plane by setting both the camera tripod's tilt, height, and direction, and the sample holder at 45 degrees.

1.6.2 Sample images.

Following are the images that we have taken the spectral cube for. These are taken by a smartphone camera.



Figure 3: Items analyzed: (a) White reference, (b) Color checker, (c) Painting, and (d) Metameric sample.

2 Results

In this section, we present the findings from our experiments and discuss their implications.

2.1 Reflectance Imaging at a Single Wavelength

Following the data acquisition phase, we utilized MATLAB to analyze the spectral images captured. Specifically, we focused on illustrating the spectral reflectance characteristics of an object at a single wavelength of 510 nm. This wavelength was chosen to highlight the differences in reflectance characteristics among the various colors. The reflectance image provides a grayscale

representation where the intensity of each pixel correlates to the amount of light reflected at this specific wavelength.



Figure 4: Reflectance images for a single wavelength: 510 nm.

2.2 Construction of RGB Images Using Selected Wavelengths

To visualize the spectral imaging data, we constructed RGB images by assigning specific wavelengths to color channels: 450 nm for blue, 550 nm for green, and 750 nm for red. This selection mirrors the peak sensitivities within the human visible spectrum.

We calculated the reflectance at each of these wavelengths for the imaged objects, normalizing against a white reference to accurately reflect the objects' true colors. In MATLAB, the **cat()** function was employed to merge these reflectance data into the three-color.



Figure 5: Composite RGB Images of the objects from spectral data.

2.3 Reflectance Spectra Analysis Across Selected Image Points

Spectral camera records reflectance by capturing light reflected from an object illuminated by a light source and converts it into electrical signals to form a hyperspectral data cube by representing the intensity of reflected light at various wavelengths for each pixel. This data is calibrated against known reference standards, like a white reference for our case, to correct for system imperfections and lighting inconsistencies.

We calculated the reflectance spectrum for every pixel in the imaged objects by focusing on five points marked on the RGB images to represent diverse spatial properties.

2.3.1 White Reference Variability

This analysis included plotting the normalized reflectance (out of 1) of the white reference plate as a function of wavelength.

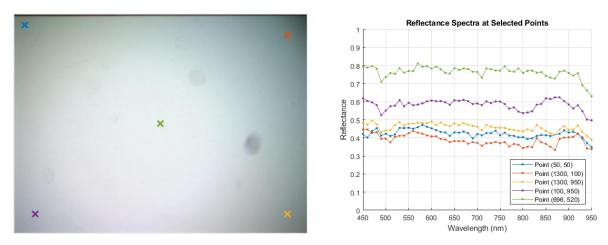


Figure 6: White reference plate with the location of selected points (left) and the reflectance spectrum for the points (right)

The spatial dimension of the images is 1040×1392 pixels. After normalization, we conveniently selected 5 points, on the edges and the center, to demonstrate the reflectance distribution. The white reference, designed for uniform reflectance, showed slight variations due to reasons that attributed to:

- System Imperfections which include minor defects in the camera optics and sensor, which
 can introduce inconsistencies in the captured data. For example, smudges on the image can
 affect reflectance values, but normalization helps mitigate this issue.
- Inherent Noise such as electronic noise from the camera sensor that can affect the intensity values recorded, especially in low-light conditions or at certain wavelengths [21].
- Uneven Illumination in the light source intensity across the imaging field can cause differences in the recorded reflectance values, even for a uniform white reference. This phenomenon is evident in Fig. 6, where reflectance values at the corners are lower (blue, red, purple, and yellow points) than those at points normal to the camera (the green point).

Then, we presented the reflectance of the other samples but using the white plate as a reference. In other words, we implemented the following formula:

$$SR_{\lambda} = \frac{Y_{\lambda}}{W_{\lambda}}$$
 (II)

where SR_{λ} is the spectral reflectance value, Y_{λ} is the raw measured data of the pixels, and W_{λ} is the raw measured data of the reference white object. We calculated the ratio between two the two measurements (sample and the reference) to primarily address the effect of uneven illumination.

2.3.2 Color checker.

The color checker analysis reveals distinctive reflectance properties for different colored squares, illustrating the variability in light absorption and reflection.

Red squares show significant reflectance peaks in the near-infrared and around 700 nm. Cyan reflects primarily in the green to blue portion. The white square demonstrates high reflectance across the spectrum, aligning with expectations for white materials that reflect a broad range of wavelengths.

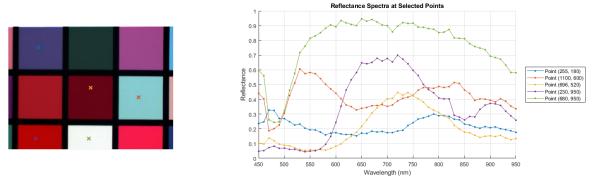


Figure 7: Color checker plate with the location of selected points (left) and the reflectance spectrum for the points (right)

2.3.3 Painting

The spectral reflectance profiles obtained from different points on the painting provide crucial insights into the types of paints used. Each color and shade in the painting reflects light at specific wavelengths, influenced by the unique chemical properties of the pigments used. This spectral variability highlights the painting's complex color composition and features the importance of spectral imaging in understanding the material and coloristic nuances in artworks.



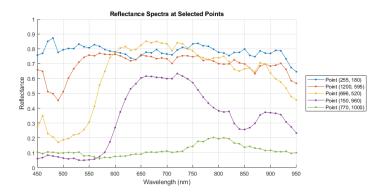


Figure 8: Painting plate with the location of selected points (left) and the reflectance spectrum for the points (right)

2.3.4 Metamerism Analysis

The reflectance spectra from selected points on the metameric plate, "UEF," reveal substantial differences in how various segments of the artwork interact with light across the spectrum. Notably, points on the green segments of the plate (290, 300) and the red segments (625, 300) exhibit different reflectance behaviors. This indicates metamerism, where these greens appear similar under normal lighting, as observed during the lab session, but distinct under other conditions after data processing through wavelength selection, as shown in Fig. 9.

The red segment has a higher reflectance peak around 700 nm, indicating stronger reflection in the red region, as expected. In contrast, the green segment shows higher reflectance around 550 nm, which corresponds to the green region. These differences in reflectance behaviors shows how the spectral properties of the segments cause them to appear similar under certain lighting conditions but reveal distinct spectral signatures when analyzed across different wavelengths.



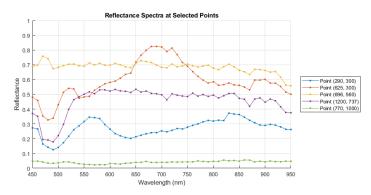


Figure 9: Metameric plate with the location of selected points (left) and the reflectance spectrum for the points (right)

3 Conclusion

Overall, this spectral imaging lab experiment successfully demonstrated the utility of multispectral imaging in distinguishing material characteristics across various samples, such as a painting, color checker palette, and metameric samples. Utilizing a Nuance multispectral camera and MATLAB for data analysis, we effectively captured and analyzed spectral images, highlighted the method's critical role in areas like art authentication and color calibration. The ability to generate RGB images and compute pixel-wise reflectance spectra provided deep understandings into material differences and metamerism and revealed potential applications in forgery detection and quality control. This hands-on experience emphasized the importance of spectral imaging in enhancing our understanding of material characteristics under different lighting conditions and provided its indispensable value in both scientific research and practical applications.

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Appendix

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