Spectral Imaging Using Basis Lights

Antony Lam[1]
http://research.nii.ac.jp/~antony
Art Subpa-Asa[2]
art@set.or.th
Imari Sato[1]
http://research.nii.ac.jp/~imarik
Takahiro Okabe[3]
http://www.pluto.ai.kyutech.ac.jp/~okabe
Yoichi Sato[4]
http://www.hci.iis.u-tokyo.ac.jp/~ysato

[1] National Institute of Informatics
Tokyo, Japan
[2] The Stock Exchange of Thailand
Bangkok, Thailand
[3] Kyushu Institute of Technology
Fukuoka, Japan
[4] The University of Tokyo
Tokyo, Japan

The spectral reflectance (SR) of objects provides innate information about material properties that have proven useful in applications such as classification, synthetic relighting, and medical imaging to name a few. General approaches to hyperspectral (HS) imaging include brute force capture of narrowband image stacks at consecutive wavelengths, use of conventional cameras with computational techniques for estimation of SR, use of specialized optics or filters, and active lighting. In particular, active lighting methods are fast and accurate. However, to our knowledge, past active lighting methods have not shown their illuminants to be optimal for SR recovery.

In our paper, we propose a new HS imaging method that utilizes optimally derived active illuminants with a standard monochrome camera. Our method is accurate and works even in the presence of unknown ambient lighting. Specifically, we make use of the well-known observation that spectra can be compactly represented by basis functions [1, 2, 3, 4]. We then show that spectral reflectance is analogous to a dot product between the light source spectrum and the surface's spectral reflectance distribution. This means that if we had a set of light sources with spectral distributions analogous to a set of basis vectors, the observed reflectance from projecting these lights onto the surface would give us coefficients. Such coefficients could then be used in conjunction with the basis vectors to recover the SR distributions of the surface.

Let us start with a definition of the reflectance model for a single surface point. Diffuse reflectance is modeled by the equation

$$I = \int s(\lambda) l(\lambda) d\lambda \tag{1}$$

where $s(\lambda)$ is the SR of the surface point at wavelength λ and $l(\lambda)$ is the illuminant at wavelength λ. From Eq. (1), we see that s and l are analogous to vectors and computation of its reflectance is analogous to a dot product. This means that if illuminant l were a basis vector, the observed reflectance I would be the projection of s onto l. In other words, I would be a basis coefficient.

So if we could project different illuminants l_m where each l_m would be equivalent to a different vector from the same basis, we could observe all the coefficients via reflectance. Having obtained all the coefficients, it would be possible to use the basis to reconstruct the SR s at the surface point. For the case of an entire surface, the same argument applies. If we could project such "basis lights" onto an entire surface and observe the reflected light using a camera, it would be possible to capture coefficients for all pixels in the scene. This would in turn permit us to recover the SR of all pixels.

The next question is, what conditions do the basis lights need to satisfy for optimal recovery using a camera? To answer this question we first define two relations.

The SR of a surface point can be expressed in terms of basis vectors as

$$s(\lambda) = \sum_{i=1}^{N} \sigma_n b_n(\lambda) \tag{2}$$

where $s(\lambda)$ is the SR at wavelength λ, $b_n(\lambda)$ is the n^{th} basis vector at wavelength λ, and σ_n is the coefficient associated with basis vector $\vec{b_n}$.

Next, we note that the the brightness $I_{p,m}$ of a given pixel p in an image taken using a grayscale camera and under lighting l_m follows the relation

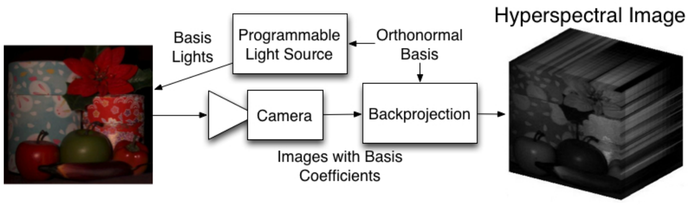

Figure 1: Flowchart of our Method

$$I_{p,m} = \int s_p(\lambda) c(\lambda) l_m(\lambda) d\lambda \tag{3}$$

where s_p is the spectral distribution at pixel p in the scene and c is the response of the camera. This is basically the same as Eq. (1) except the camera response is also taken into account.

If we substitute s_p from Eq. (3), with Eq. (2) we get the relation

$$I_{p,m} = \sum_{i=1}^{N} \sigma_n \int b_n(\lambda) c(\lambda) l_m(\lambda) d\lambda = \sum_{i=1}^{N} \sigma_n g_{n,m} \tag{4}$$

The intensities $\vec{I_p} = [I_{p,1} ... I_{p,M}]^T$ of pixel p under all lightings l_m from 1 to M can also be expressed in matrix form as

$$\vec{I_p} = \begin{bmatrix} g_{1,1} & \cdots & g_{N,1} \\ . & & . \\ . & . & . \\ . & & . \\ g_{1,M} & \cdots & g_{N,M} \end{bmatrix} \begin{bmatrix} \sigma_1 \\ . \\ . \\ . \\ \sigma_N \end{bmatrix} = G\vec{Q} \tag{5}$$

From Eq. (5), we see the basis coefficients $\vec{Q}$ can be solved for from the pixel intensities $\vec{I_p}$ and G. Ideally, if matrix G, has a condition number of 1, $\vec{Q}$ can be solved for reliably. We show in the paper that one way to satisfy this requirement is to use an orthonormal basis.

One issue is that an orthonormal basis would typically contain negative values, which are not physically plausible as light sources. In our paper, we show that negative light can be simulated and as an added benefit of this procedure, the effects of unknown ambient light can be canceled out. The experimental results also confirm that our method is able to accurately recover the spectral reflectance of entire scenes even under unknown ambient light.

[1] Te-Won Lee, Thomas Wachtler, and Terrence J. Sejnowski. The spectral independent components of natural scenes. In *First IEEE Intl. Workshop on Biologically Motivated Computer Vision*, BMVC, pages 527–534, London, UK, 2000. Springer-Verlag. ISBN 3-540-67560-4.

[2] Laurence T. Maloney. Evaluation of linear models of surface spectral reflectance with small numbers of parameters. *JOSA A*, 3(10):1673–1683, Oct 1986.

[3] David H. Marimont and Brian A. Wandell. Linear models of surface and illuminant spectra. *JOSA A*, 9(11):1905–1913, Nov 1992.

[4] J. P. S. Parkkinen, J. Hallikainen, and T. Jaaskelainen. Characteristic spectra of munsell colors. *JOSA A*, 6:318–322, 1989.