Spectral Probing

Multi-Spectral Imaging by Optimized Wide Band Illumination

Cui Chi*
Tsinghua University
cch2000@umd.edu

Moshe Ben-Ezra
Microsoft Research Asia
mosheb@microsoft.com

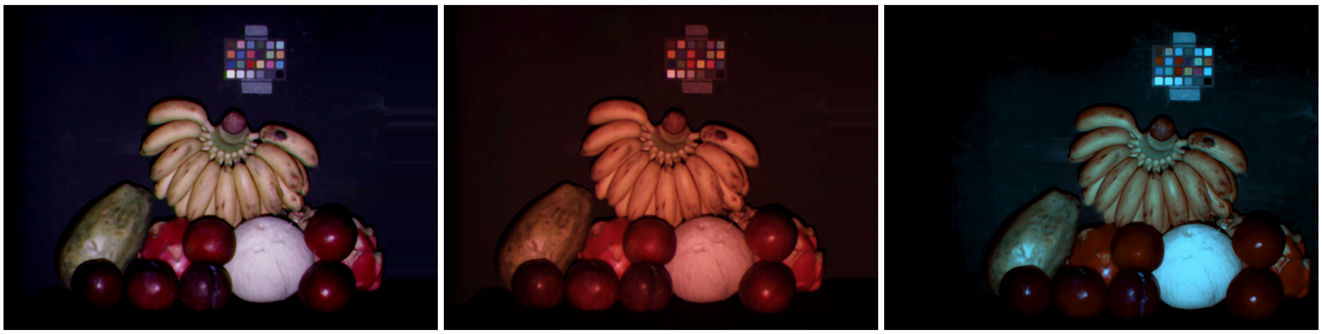


Figure 1. **Synthesized color images from computed multi-spectral data. Still-life scene with synthesized white illumination (left), tungsten illumination (middle) and theater blueish illumination (right)(roscolux# 72 filter).**

Abstract

We present a novel active imaging approach that uses optimized wide band filtered illumination to obtain multi-spectral reflectance information. Our optimization algorithm utilizes light source and camera spectral information in order to maximize the signal strength and the robustness to noise. Through the use of active wide band illumination, our system can obtain material reflectance information in the presence of moderate (indoor) unknown ambient illumination. Our method is very simple and does not require special equipment. It can be used by professional and amateur photographers alike to obtain material properties and to synthesize captured scenes under arbitrary illumination.

1 Problem, Contribution and Limitations

We seek a very simple approach to multi-spectral imaging to be used by amateur and professional photographers in everyday environments without special equipment. Multi-spectral reflectance data allows better color constant rendering and spectral re-lighting under arbitrary illumination, which is important for applications such as recording and archiving for cultural e-Heritage and digital museums[15].

We address the following problems: (i) Filter Selection - Optimal filter selection for digital photography is a difficult problem, even for trichromatic imaging [9]. In this paper, we selected 16 of 208 possible filters. (ii) Ambient Illumination - analyzing the spectral properties of the radiance emitting from an object using a passive multi-spectral camera with wide field of view [17, 18] does not usually reveal the actual reflectance properties of the material as the irradiance at each object point is generally unknown[1]. Moving the object to a dark room or scanning it using a spectrometer that measures a single point (while shielding it from stray light) is time consuming and may not always be practical.

In this paper we approach these problems by *probing* the scene using active illumination. The main contributions of this paper are: (i) we provide a truly simple and affordable[2] approach to multi-spectral imaging using only a camera, a light source (slide projector or a flash) and a set of theatrical color filters. (ii) we propose an algorithm for selecting an optimized set of filters from a large set of wide band filters. (iii) we show that by modulating the illumination we can greatly reduce the effect of ambient light, including spatially varying ambient illumination.

The main limitation of our active method, is that it cannot be used to photograph distant objects, such as landscape, and cannot be used in direct sunlight. However, our filter selection method is still applicable to these circumstances.

Related work

Multi-spectral imaging is an extremely wide field of research ranging from material classification [3] and color measurement [20] to terrestrial imaging [22, 21] and astronomical imaging [6]. In this paper we only focus on aspects of multi-spectral imaging that are related to computer vision and image based rendering. In particular, we

*This work was done while Cui Chi was a visiting student at Microsoft Research Asia.

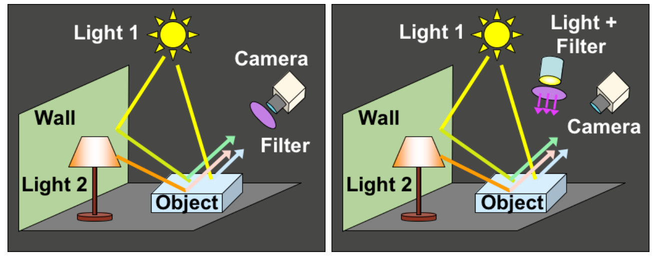
[1] This would require complete knowledge about the light sources, geometry of the scene and BRDF of the object.

[2] The entire set of filters used in this paper costs less than USD$1.

are interested in modeling, filter selection, robustness to noise, color constancy[4] and spectral re-lighting. Abrardo et al. [1] showed that color constancy can be obtained from multi-spectral images using only seven spectral channels and finite-dimensional linear models. Maloney et al. [13] further enhanced model based spectral analysis. Jaaskelainen et al. [11] have used principal component analysis (PCA) on two data sets (Munsell colors and naturally occurring spectral reflectances) to construct a vector-subspace model that can be used to model both data sets.

More recently, Connah et al. [2] compared the performance of several linear methods for reflectance estimation using digital cameras. They concluded that smoothness maximization provides the best performance. Imai et al. [10] compared narrow band and wide band filtering for multi-spectral imaging and showed that although the narrow band is theoretically more robust, good and sometime superior results were obtained using a wide band filter set. This result supports our selection of wide band filter set, though our primary reason is energy related [19]. Imai et al. [9] also addressed the problem of selecting 5 filters out of 33 for a 5-channel multi-spectral camera. To solve the combinatorial selection problem in reasonable time they used a heuristic based on previous results.

A closely related work is the use and optimization of tunable filters for multi-spectral imaging [5]. In contrast to these methods that use special devices for *constructing* the optimized filters, we select an optimized subset of filters from a larger set.



(a) (b)

Figure 2. **(a) Conventional multi-spectral methods use a set of filters that are placed (either temporally by switching filters, or spatially as in Bayer pattern) in front of the sensor. With multiple light sources, and inter reflections it is very difficult to obtain the reflectance information of the material (decoupled from illumination variations). (b) In contrast, Spectral Probing places the filters in front of an additional light source, thus significantly improving the ability to recover material reflectance information.**

2 Method

2.1 Model and Analysis

We model the radiometric response of pixel (x, y) as:

$$\rho_k^{xy} = t \int R_k(\lambda) S^{xy}(\lambda) E^{xy}(\lambda) d(\lambda) + N(\alpha t, \alpha t), \quad (1)$$

where $E^{xy}(\lambda)$ is the spectral distribution of the incident flux (irradiance) at the world point P corresponding to pixel (x, y), $S^{xy}(\lambda)$ is the reflectance spectral distribution at P, $R_k(\lambda)$ is the camera response function at channel k, and t is the integration time. $N(\alpha t, \alpha t)$ is additive Gaussian noise with mean and variance proportional to the integration time. This approximates the sensor's Poisson distributed additive[3] noise (mostly dark current).

We now add a light source with known spectral distribution $L(\lambda)$ and a filter with known spectral transmittance distribution $\Phi_i(\lambda)$ to the model. However, instead of putting the filter in front of the lens, as is usually done for multi-spectral imaging, *we put the filter in front of the new light source*. Assuming that no shadows are casted by the new light source[4], the irradiance at the P is now composed of two components: ambient illumination $A^{xy}(\lambda)$, and the additive light $L(\lambda)$ modulated by the filter $\Phi_i(\lambda)$. The added component is assumed to be unaffected by location of P[5]:

$$\begin{aligned} \rho_{k,i}^{xy} &= t_i \int R_k(\lambda) S^{xy}(\lambda) \left[A^{xy}(\lambda) + \Phi_i(\lambda) L(\lambda) \right] d(\lambda) \\ &+ N(\alpha t, \alpha t), \end{aligned} \quad (2)$$

where t_i is the integration time used with filter Φ_i.

We now subtract two measurements taken with two different filters i, j and normalized by the (possibly different) integration times t_i, t_j:

$$\begin{aligned} t_j \rho_{k,i}^{xy} - t_i \rho_{k,j}^{xy} &\approx t_j t_i \int R_k(\lambda) S^{xy}(\lambda) \Phi_i(\lambda) L(\lambda) d(\lambda) \\ &- t_i t_j \int R_k(\lambda) S^{xy}(\lambda) \Phi_j(\lambda) L(\lambda) d(\lambda) \\ &+ N(0, 2\alpha t_i t_j). \end{aligned} \quad (3)$$

This eliminates any (linear) effect caused by the ambient light component, which can be quite complex, and reduces the mean of the additive noise. The cancelation of the (linear) ambient light component would not be possible had the filter been placed in front of the lens, as the unknown ambient illumination component would be affected by the filter as well. Inter-reflections (and translucency) of the new light source do exist and affect the accuracy of the measurement. This limitation can be relaxed if the light source is a projector by separating the direct and indirect components as shown by Nayar et al. [14].

Placing the filter in front of the light has an undesirable consequence. The filter $\Phi_i(\lambda)$ attenuates the intensity of the light source $L(\lambda)$, but does not affect the intensity of the ambient light. This rules out the use of narrow band filters $(10\mu m \ldots 20\mu m)$, due to their low intensity relative to the ambient light.

[3]This simple model does not include multiplicative noise.

[4]Flat world model, or coaxial illumination.

[5]Far light source, and flat world assumption or coaxial illumination.

Finding a sufficient number of significantly different wide band filters is not an easy task. Luckily, since the filters are placed in front of the light source, they need not have optical quality surfaces. We choose Roscolux theatrical filters[16]. These filters are designed for lighting applications in theaters and are available with over over 230 different (known) spectral transmission distribution. We now face the problem how to characterize a good selection and how to select a small subset (8-16) from a huge space of $\binom{230+}{8\ldots16}$ possible selections.

2.2 Filter Selection and Optimization

Trichromatic filter selection optimization is mainly concerned with maximizing light transmittance efficiency and matching the human eyes response. For our purpose, we are mainly concerned with the numerical stability of the complete system, including the light source, filter set and camera response. We seek to minimize the condition number of M in the resulting discrete version $S = MX$, where S is the recovered reflectance, $M = M_{n\times n} = \left[R_\lambda\left(\Phi_\lambda^i - \Phi_\lambda^j\right)L_\lambda\right]^{-1}, \ 1 \leq i \leq n, \ j = i+1$ is the transformation matrix[6] and X is the measurement vector $\rho_i^{xy} - \rho_j^{xy}$, of equation 3 (scale omitted for clarity).

We seek to minimize:

$$k(M) + w\bar{T}^{-1}, \tag{4}$$

where $k(M)$ is its condition number of M, $\bar{T}$ is the average transmittance of the selected filter set used to favor better transmittance, and w is a small weighting factor.

Clearly the number of combinations $\binom{230+}{16}$ is too large to be directly evaluated using an exhaustive search. Even after discarding filters with very low average transmittance we are left with $\binom{228}{16}$ possible combinations. This is a difficult non-linear optimization problem.

Because a selection can be represented as a string of zeros and ones, or in a more compact way, as a string of indices, selection problems lend themselves naturally to optimization using genetic algorithms. The DNA represents a specific selection of filters, a crossover is a switching of filter subsets between two selections, and a mutation is the substitution of a single filter with another. We followed the genetic algorithm framework presented in [12]. We used a very simple genetic algorithm summarized by 'Algorithm-1' below. We ran the algorithm for a relatively long time (a few days) to obtain the filters used in this paper.

Algorithm 1

Input:

- L - illumination source spectral distribution
- Φ - a set of filter spectral transmission
- R - camera spectral response
- N - maximum number of iterations
- S - population size
- K - reproduction (keep) rate
- C - crossover rate
- M - mutation rate

Output:

- Selected filter set.

Processing:

1. Select at random population of size S from Φ.
2. Sort results in descending order using Equation 4.
3. Copy the best $K\%$ of S to the next generation.
4. Crossover $C\%$ random pairs based on fitness and insert them into the next generation.
5. Mutate $M\%$ random selected filters based on fitness and insert them into the next generation.
6. Repeat from step 2 until maximal number of iteration is reached.

[6] In practice we use M^{-1} to avoid matrix inversion.

Setup	Condition No.
Min Random Selection	2063
Filter Only	1119
Tungsten Illumination Result	348
Tungsten+Correction	208

Table 1. **The performance of our filter selection algorithm. Random Selection: minimum condition number of a large set of random selections of filters. Filter Only: optimization without considering the specific light and camera response. Tungsten Illumination Result: optimization result for tungsten illumination. Tungsten+Correction: optimization result with illumination corrective filter. The overall condition number improved significantly.**

Finally, for tungsten illumination case, we added a balancing blue filter to boost its color temperature. We manually selected one filter from a set of five filters. This filter was used in conjunction with each of the other filters. Table 1 shows the result of our optimization process. We can see that our optimization algorithm considerably reduces the condition number of the system, we can also see that better results were obtained when using a corrective illumination filter.

3 Testing

We tested our method using simulations, a tungsten (slide projector) light source, and a xenon (flash) light source. The tests were conducted indoors with ambient illumination conditions varying from controlled illumination inside a darkroom to uncontrolled illumination of an open-space cubical.

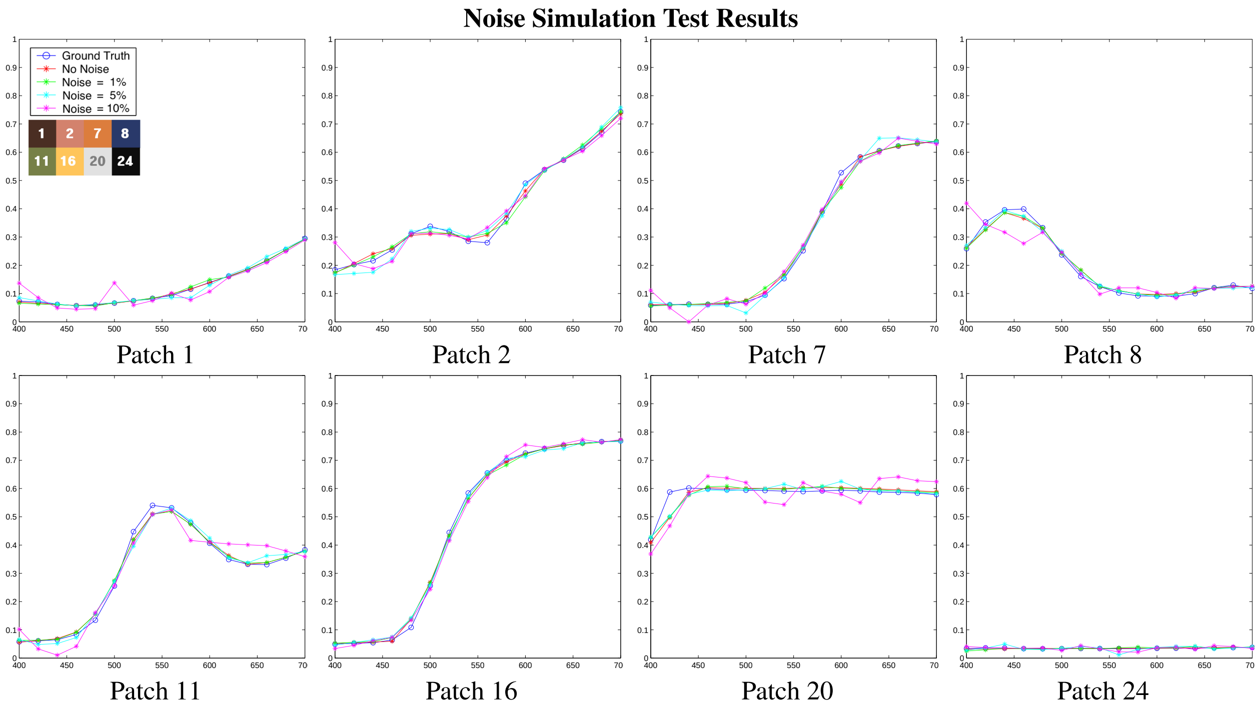


Figure 3. **Noise simulation result: Ground truth and recovered reflectance curves of various samples (from the Macbeth color checker) under different noise conditions. Corresponding patch colors are shown at the top left corner.**

3.1 Simulation Tests

We simulated the imaging process using the known spectral distribution of tungsten illumination, the Macbeth color checker reflectance and the response of a Sony ICX424AL monochromatic sensor. We approximated Poisson noise with Gaussian noise having the same mean and variance. We tested our system using zero noise and noise level of 1%, 5% and 10% of the signal level. We simulated a set of 16 filters that were selected by our algorithm and used truncated SVD[8] to solve for reflectance. Simulation results are shown in Figure 3. Our method recovers the reflectance of the Macbeth color checker with average RMS error ranging between 1.8% for 1% noise level to 3.3% at 10% noise level, respectively.

3.2 Real Image Tests - Macbeth Color checker

In this test we used a conventional 35mm slide projector as our light source. We used a monochromatic camera, and a set of 16 filters plus a correction filter for the tungsten illumination (as described earlier). We placed the filter set in the projector cartridge and the correction filter in front of the projector lens and took a sequence of images, each with different added illumination. Throughout the experiment we left the room fluorescent light on to add relatively strong and unknown ambient illumination. We then computed the reflectance using truncated SVD (with dimension 12). The results are shown in Figures 4,5 and 6.

Figure 4 shows the best and the worst results of the test (only one grey scale patch is shown as all were good). We can see that while there is a problem at the far red part of the spectrum in some of the patches, the curve generally fits and the overall average RMS error was 7%. Figure 5 is given as a reference and shows the resulting curves without applying differences shown in Equation 3. The ambient light drastically reduces the quality of the results. Finally, we relight the Macbeth color checker using our measurements and compared the results to the ground truth rendering. The results are shown in Figure 6. The computed results, though not identical, are very close to the ground truth rendering.

3.3 Real Image Tests - Natural Objects

In this test we captured a multi-spectral image of an assortment of fruits in a similar way to the previous test. We compared real images captured by a Nikon D70 camera with images computed from multi-spectral data. We computed images for tungsten illumination and flat spectra and applied the non-linear gamma function of the Nikon-D70[7] to the result. Figure 7 shows the comparison result. The computed pictures, though not identical to the real Nikon images that were more greenish/yellowish, look similar and quite natural. We also show the reflectance curve of part for the scene in Figure 8.

3.4 Real Image Testing - Xenon Illumination

For our next test we used a Xenon light source (Nikon camera flash) and an RBG camera (Nikon D70). We used our algorithm to select a new set of filters using the camera's

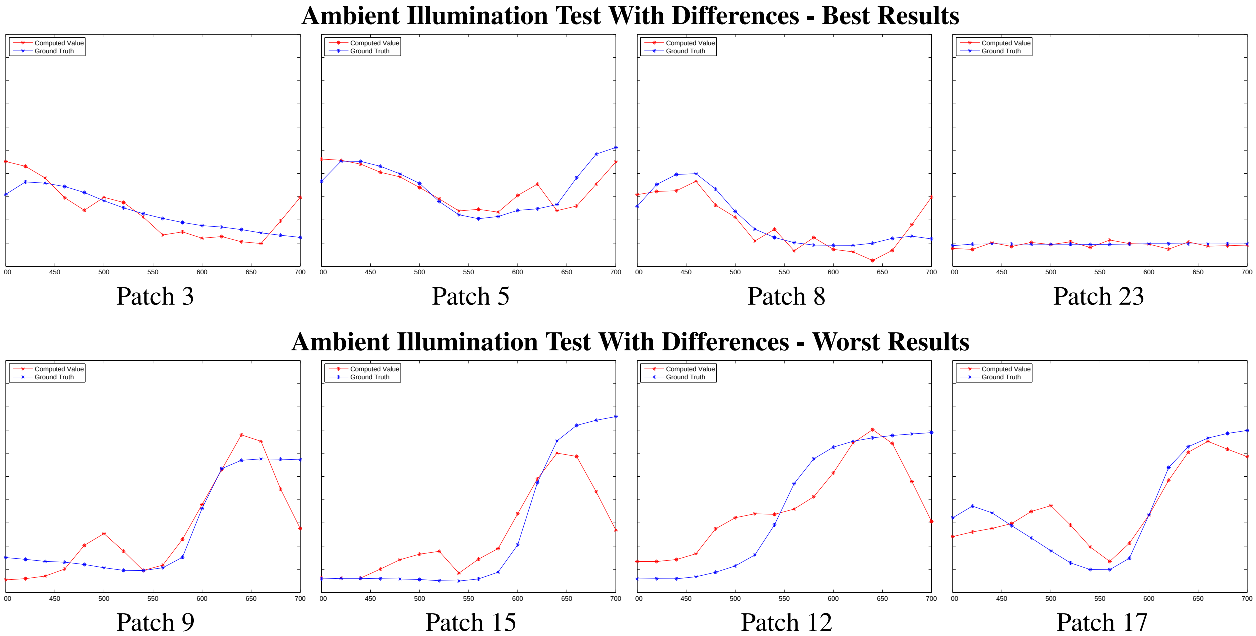


Figure 4. **Best *and Worst* results of real Macbeth color checker test with unknown ambient illumination. Inaccuracies occur mostly at the far red range.**

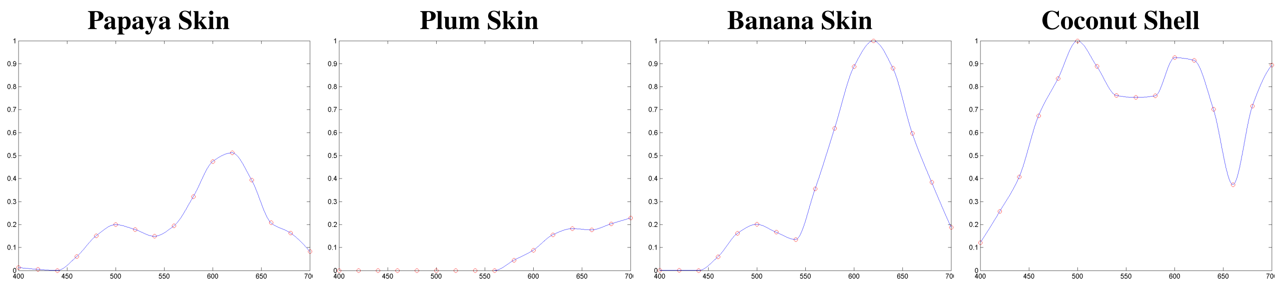


Figure 8. **The recovered reflectance distribution of some parts of the fruits. Both spectral distribution and relative albedo are recovered.**

trichromatic response, and we selected only three filters (the minimum number if we wish to use differences and obtain multi-spectral information).

Figure 10 shows images captured using three different filters (used in conjunction with the camera's RBG filters), a captured white-balanced image and a synthesized flat illumination image. As seen in the figure, the computed image looks almost identical to the white-balanced captured image. The advantages of our approach over traditional camera pre-set white balance are (i) neither calibration nor mode selection by the photographer is needed, and (ii) our methods works on a pixel to pixel basis. It is therefore applicable to uneven complex illumination (for example a scene is lit through a window and by a table lamp). Spatially varying white balancing is not possible using traditional camera white balancing, which is a global operator.

Two filters are enough to obtain a white balanced image under unknown ambient illumination as only RGB channel information needs to be recovered. The third filter allows us to do spectral-relighting using multi-spectral information. Figure 2 shows some synthesized colors images using the captured multi-spectral data.

4 Applications

As only few simple and very affordable filters are needed, our method can be used in professional studio photography, as well as amateur photography. Professional studios already have multiple light sources (strobe and continuous), and some even have computerized illumination systems. It is therefore very simple to add a few filters and obtain much richer post-processing capabilities.

Amateur photographers can use a multi-flash system as the hypothetical flash shown in Figure 9 (or be embedded in the camera itself). This hypothetical flash is set to work with the camera continuous shooting mode. A burst of three images can be captured in less than a second. The images can be processed either by the camera or by an external computer.

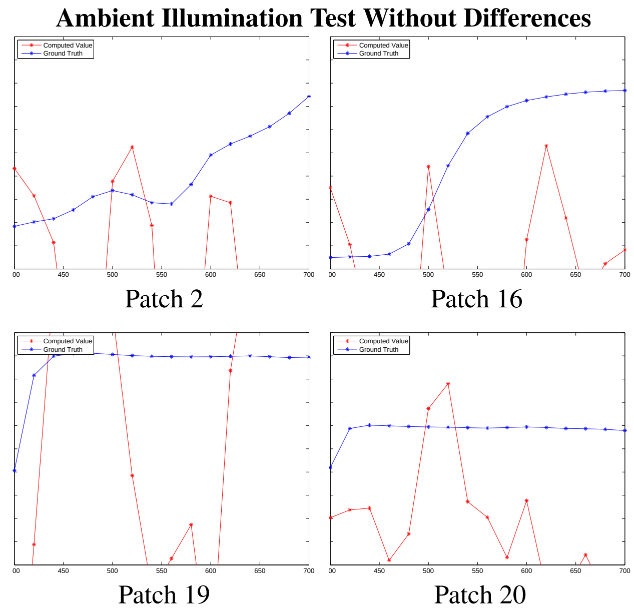


Figure 5. **Macbeth color checker test results with unknown ambient illumination without using differences. The unaccounted-for ambient light drastically degraded the accuracy of the result.**

A typical application will need to align the images (if not captured using a tripod) and then allow the user to select different illuminations and camera (or film) response function [7] from a predefined set (or create new ones). Figure 12 shows a very simple Matlab prototype that allows the user to select and manipulate light spectra and camera (or film, as some photographers may cherish a certain film with traditional look and feel) responses and create new spectral relit images. Although very simple, these effects cannot be reproduced as easily and reliably by much more complex software systems such as Photoshop.

A more sophisticated program may be able to use multiple light sources with different spectral distributions and 3D scene information to create true relighting of a scene in a "virtual light studio".

5 Conclusion

We present a very simple, affordable and yet effective method for multi-spectral imaging using active illumination. Our method requires simple theatrical filters that are selected by a genetic algorithm from a very large space of possible combinations to match the added illumination and the camera spectral characteristics.

We show that by modulating the illumination with color filters in front of the illumination source we can significantly reduce the effect of the ambient illumination. These filters can work in conjunction with the camera's RGB filter set to provide better spectral resolution (or reduce the number of illumination modulating filters).

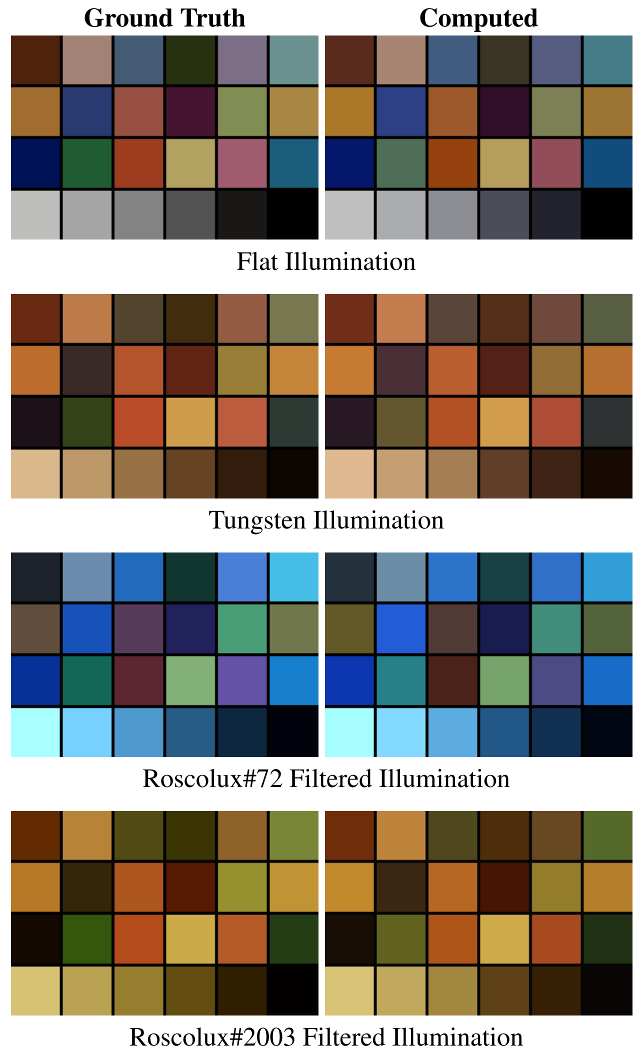


Figure 6. **Rendering of the Macbeth color checker under various illuminations for ground truth data (left) and our captured multi-spectral data (right). The result, though not completely identical, is very close.**

We showed that our optimization algorithm significantly reduces the condition number of the resulting equation set. We presented simulated and real tests showing the effectiveness of our approach.

Finally, we presented a possible application in which a multi-flash system can be used to capture multi-spectral information that can be used for color balancing and for color relighting with the help of a simple "virtual light studio" prototype. This enables the photographer to mimic the look and feel of different light sources and different cameras or films using digitally captured images.

Acknowledgement

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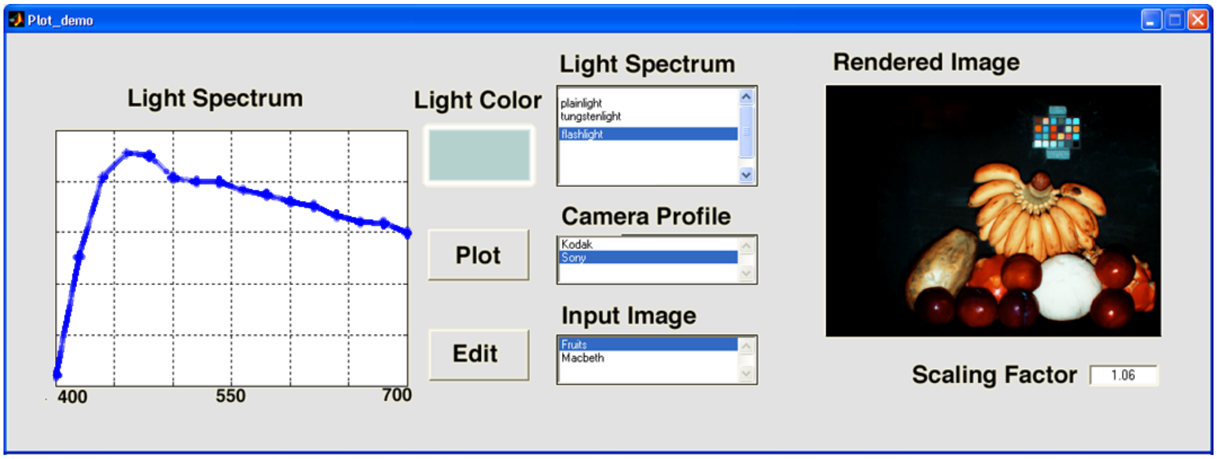

Figure 12. **Our interactive user interface prototype. The user can select predefined light spectra, and camera profiles, and can also manually edit the light spectrum and create arbitrary illumination effects. A more sophisticated program may be able to use multiple light sources with different spectral distributions and 3D scene information to truly relight a scene in a virtual light studio.**

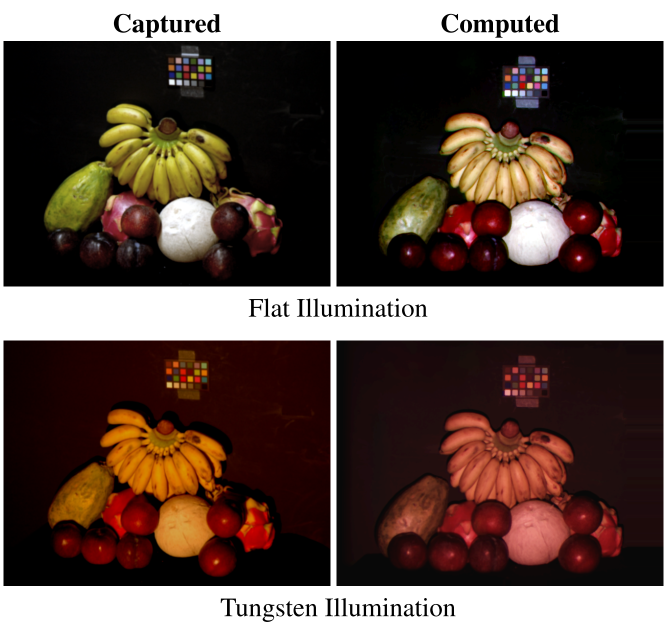

Figure 7. **Real images taken by Nikon D70 under flat and tungsten illumination (left) and computed images using our captured data and estimated camera spectral response. The images are similar, though the real D70 images are more greenish.**

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Figure 9. **An hypothetical multi-flash system. The flash works in conjunction with the camera continuous shooting mode to capture three images, each with different added illumination.**

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Figure 10. **Balanced illumination image synthesis. Top: Three input images used for multi-spectral computation. These images were captured under unknown ambient illumination (open space room) and are clearly not balanced. Bottom left: captured image using the camera (Nikon D70) while balance calibration. Bottom right: computed flat illumination from multi-spectral data (no calibration was used).**

Figure 11. **Synthesized images created from computed multi-spectral data and different light spectra. A range of strong and subtle color variations are easily produced.**

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