

An LED-based lighting system for acquiring multispectral scenes

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ABSTRACT

The availability of multispectral scene data makes it possible to simulate a complete imaging pipeline for digital cameras, beginning with a physically accurate radiometric description of the original scene followed by optical transformations to irradiance signals, models for sensor transduction, and image processing for display. Certain scenes with animate subjects, e.g., humans, pets, etc., are of particular interest to consumer camera manufacturers because of their ubiquity in common images, and the importance of maintaining colorimetric fidelity for skin. Typical multispectral acquisition methods rely on techniques that use multiple acquisitions of a scene with a number of different optical filters or illuminants. Such schemes require long acquisition times and are best suited for static scenes. In scenes where animate objects are present, movement leads to problems with registration and methods with shorter acquisition times are needed. To address the need for shorter image acquisition times, we developed a multispectral imaging system that captures multiple acquisitions during a rapid sequence of differently colored LED lights. In this paper, we describe the design of the LED-based lighting system and report results of our experiments capturing scenes with human subjects.

Keywords: Multispectral imaging, LED illumination

1. INTRODUCTION

Multispectral scene data are useful for many applications in color imaging, including classification, imaging systems simulation and scene rendering. For example, the availability of multispectral scene data makes it possible to simulate a complete imaging pipeline for digital cameras, beginning with a physically accurate radiometric description of the original scene, followed by optical transformations that create irradiance signals, sensor transduction models that convert photons to electrons, and image processing algorithms that generate digital images that can be displayed¹.

Multispectral scene data can be described as a 3D matrix or datacube in which each voxel is addressed by its 2D spatial coordinates and a third wavelength dimension. For example, a scene with 1024 x 1024 spatial samples and 31 wavelength samples (400 – 700 nm sampled every 10 nm) will constitute a 1024 x 1024 x 31 datacube. An RGB image of the same scene is a 1024 x 1024 x 3 datacube. Hence, a significant amount of scene spectral information is lost when a color digital camera captures an image of a scene.

Mathematically, the multispectral signal at each point in a scene is a vector, x , that is estimated by solving the equation

$$y = Ax + \eta, \quad (1)$$

where y is a vector with n measurements, A is a measurement matrix and η is measurement noise. For example, consider an RGB camera with calibrated spectral sensitivities ranging between 400 and 700 nm, sampled every 10 nm. The measurement matrix A is 3 x 31. The multispectral signal x at each sampled point is 31-dimensional vector. The data captured by the camera, y , is a 3-dimensional vector. It is not possible to recover a 31-dimensional vector with only three measurement samples, y . In other words, the problem of recovering x from y is an under-constrained problem with many possible solutions. The goal of multispectral imaging is to increase the dimensions of the measurement matrix, A , and to constrain the space of solutions by using statistics about natural spectra.

One way to increase the dimensions of the measurement matrix, A , is to capture multiple images of a scene using a color digital camera with many different color filters²⁻⁷. The combined spectral transmissivities of the filters and the spectral

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sensitivities of the 3 color sensors form the matrix A . Another approach is to acquire multiple images with different illuminants⁸. In this approach, the combined spectral power distributions of the illuminants and the spectral sensitivities of the 3 color sensors form the matrix A . Both schemes require long acquisition times and are best suited for static scenes. In scenes where animate objects are present, movement leads to problems with registration and methods with shorter acquisition times are needed.

Certain scenes with animate subjects, e.g., humans, pets, etc., are of particular interest to consumer camera manufacturers because of their ubiquity in common images and the importance of maintaining colorimetric fidelity for skin. To address the need for shorter image acquisition times, we developed a multispectral imaging system that makes multiple acquisitions while being illuminated by a rapid sequence of different LED lights. The combined spectral response functions of the LEDs and the camera form the matrix A and the multispectral image is computed by solving Eq. (1). In this paper, we describe the design of the LED-based lighting system and report results of our experiments capturing scenes that include human subjects.

2. LED LIGHTING SYSTEM

The LED-based lighting system¹⁴ we prototyped consists of an array of 216 LEDs with clusters of 8 different types of LEDs mounted on a printed circuit board (PCB) (Figure 2a). The board is mounted between a pair of acrylic boards. The front-facing board acts as a diffuser. Figure 2b shows a side view of the LED imaging system. Of the 8 types of LEDs, 5 operate in the visible range of wavelengths (400-700 nm), one LED type operates in the UV range (380 nm) and 2 LED types operate in the near infrared range (700-1100 nm).

Here, we report our work with the visible range LEDs in the lighting system. The five visible-range LED types are from the Philips 1 W Luxeon series (designated Royal Blue, Cyan, Green, Amber, and Red). Figure 2c shows the spectral power distributions (SPD) of these LEDs.

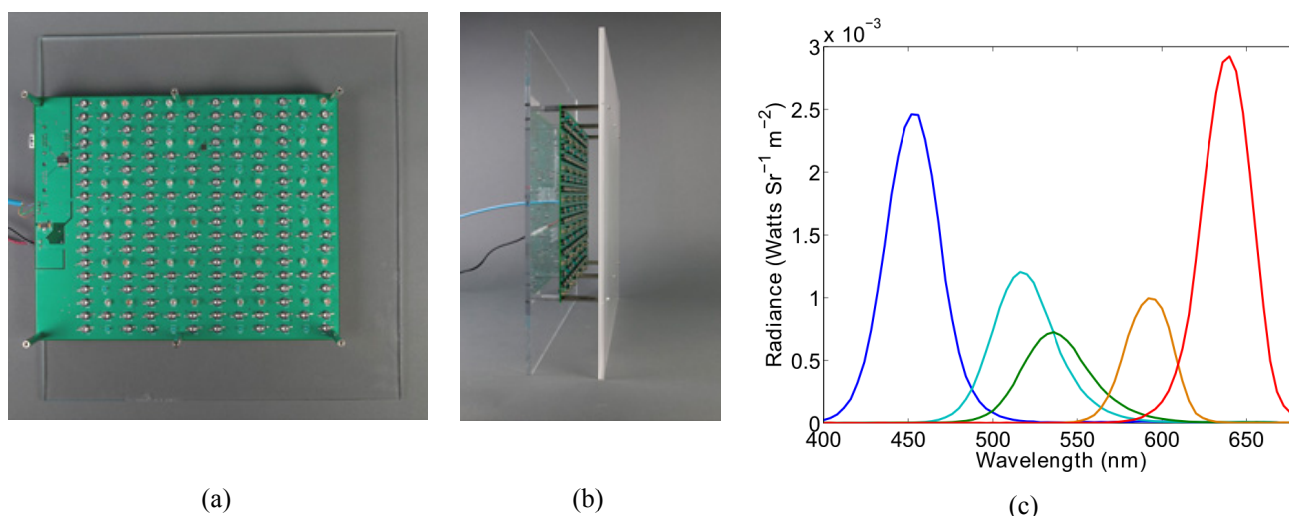


Figure 2. (a) The LED-based lighting system board showing placement of LED arrays (b) side view of lighting system showing the acrylic front plate used as a diffuser (c) Spectral power distributions of the different LED types used in the lighting system.

The LED lighting system can be programmed to change switching and delay times, shutter control of a camera, switching sequence, etc. The LED lighting systems is capable of switching times as fast as 100 ms and allows one LED type to remain on for a maximum of 30s. The system also allows for PWM operation for sustained periods of time. Temperature sensors allow automatic shut-off in case the system overheats. This functionality is achieved with an Atmel

AVR ATmega1280/2560 microcontroller which supports 12 PWM channels, has 2 UARTs (for communication with a PC), and several general purpose IOs that are used to control a camera and for status indicators.

3. IMAGE ACQUISITION

We coupled the LED-based lighting system to a Nikon D2xs digital SLR camera with a Nikon Nikkor 50 mm $f/1.8$ prime lens. The Nikon D2xs camera sensor contains a Bayer mosaic with two green, one red and one blue photodetector type in a 4,288 x 2,848 grid. The Nikon D2Xs has a 12-bit ADC and makes available camera RAW images that have not been processed for color-balancing, gamma, etc. The spectral transmittances of the color filters of this camera were experimentally determined and are shown in Figure 3a.

Figure 4b shows the spectral sensitivities of 8 of the 15 filters (camera color sensitivity modulated by the LED SPDs) that result by combining 3 color filters (RGB) with the 5 visible-range LEDs. One acquisition with the LED imaging system gives a 3-plane image that is separated to give 3 image planes that each represent a measurement with one of the filters shown in Figure 3b. In practice, for reasonable exposure durations for animate subjects, only 8 of these channels (shown in Figure 4b) give useful signals; the rest have poor SNR.

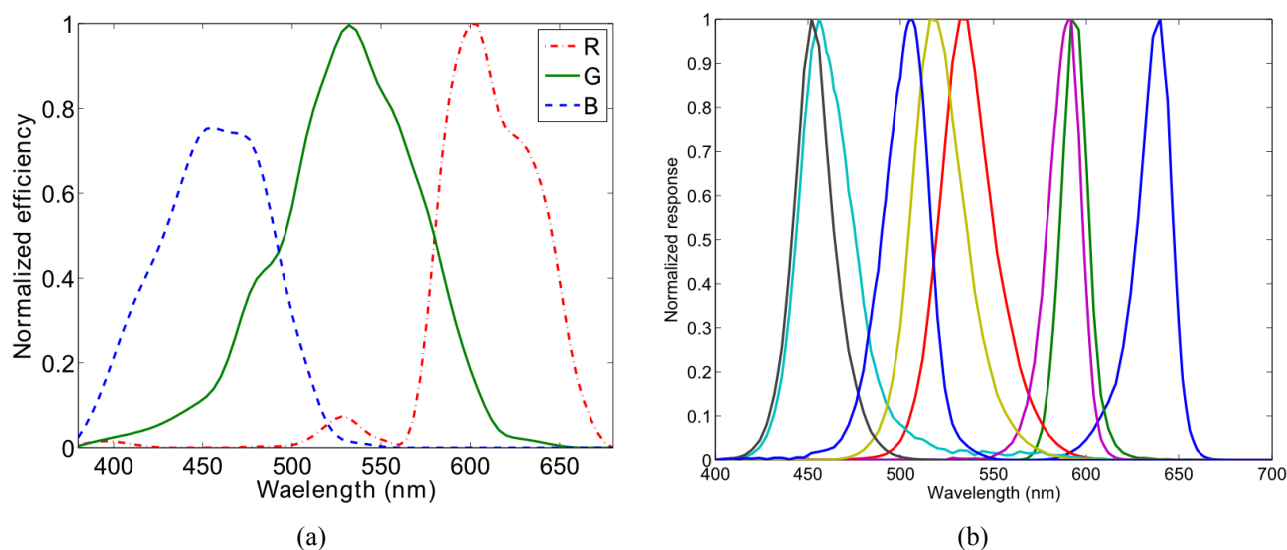


Figure 3. (a) Normalized spectral efficiencies of the RGB filters of the Nikon D2xs camera with the Nikon Nikkor 50 mm lens at $f/4$ (b) The normalized responses of the 8 different light and camera-filter combinations of the LED lighting system that give useful signal.

The different LED types are arranged on a printed circuit board. Since the LED types are shifted with respect to each other, the light pattern due to each LED type is different. Furthermore, the beam widths of the LED types are not similar, the placement of the camera atop the lighting system and there is a cosine fall-off in irradiance due to the camera lens. To account for these effects, we captured defocused camera images of a large gray uniform chart illuminated by each of the different LED types. We found the best 2nd order polynomial function describing the intensity fall-off across each of the calibration images and used the functions to spatially calibrate the camera images. Figure 4 illustrates this calibration step. Figure 4a shows a defocused image of the gray background (the blue channel of the D2xs camera) captured with the blue LED only. Figure 4b shows the scaling factors at each spatial location used to adjust for spatial variation in irradiance. Each of the 8 image planes is appropriately calibrated.

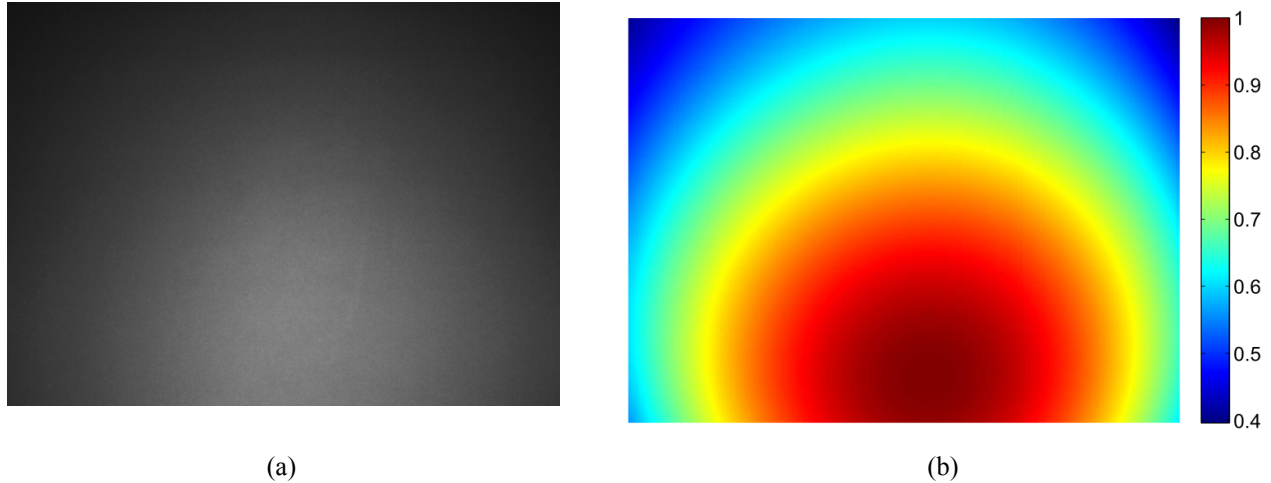


Figure 4. (a) Blue plane of a defocused image gray chart acquired by turning on the blue LEDs (b) A 2D fit to a 2nd order 2D polynomial that gives correction factors for accounting for spatial intensity variations.

Figure 5a shows the front-view of the LED imaging system with attached camera, Figure 5b shows a side view. The shutter for each image was triggered by the same signal that controlled the LED lights. The distance between the subjects and the LED lighting system affects the exposure duration. In our experiments, the system was set up so that the system's field of view included a subject and a standard color calibration target (Figure 5c). The camera exposure duration was determined by the longest shutter speed for which none of the camera RGB channels were saturated.

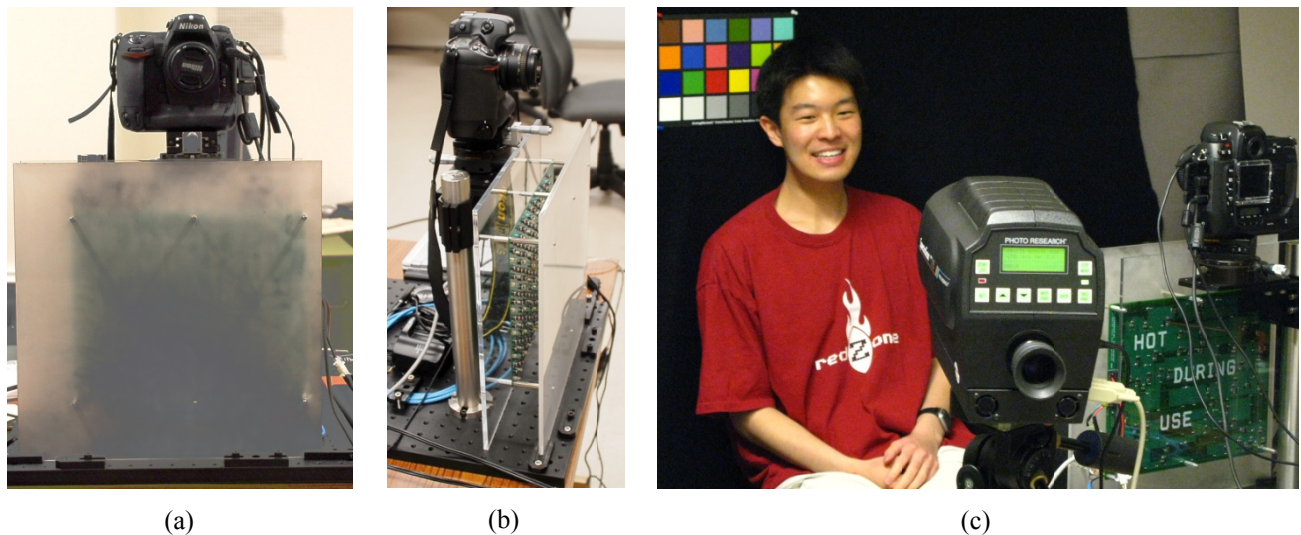


Figure 5. (a) Front view of the LED lighting system with camera (Nikon D2xs) (b) side-view (c) The system in use for image acquisition.

4. IMAGE ESTIMATION

In the context of our LED imaging system, the multispectral signal x in Eq. (1) is a reflectance factor associated with sampled points in the scene. The measurement matrix A is an 8×31 matrix; its rows are 8 of the 15 combined camera-RGB and LED response functions. The problem of recovering x from y is an under-constrained problem with many

possible solutions. There are several ways to find stable solutions to such ill-posed problems. In general, we must find a way to constrain the space of solutions by using knowledge of the nature of spectra.

A well-known property of reflectance spectra is that they are essentially lower-dimensional signals. Reflectance is typically considered to be well sampled when sampled 31 times in the interval [400,700] nm. It has been shown that most spectra may be represented by coefficients corresponding to as few as 6 basis vectors¹⁵ (let P be such a basis). This observation leads to methods for solving Eq. (1) by constraining the estimate of x to lie in the space spanned by P . The problem of reflectance estimation has also been addressed with the Wiener filtering approach¹⁶.

Another recent approach for recovering spectra based on the theory of compressed sensing¹⁷ relies on the sparsity of object reflectance spectra in certain bases¹⁸. Sparsity implies that there exists a transform basis, say P where object spectra are represented accurately with only a few coefficients. Mathematically, for $x \in \mathbf{R}^k$, such that $\|x - Pa\|_2 < \varepsilon$, where only m elements of a are non-zero, and $m \ll k$. For such spectra, an $l1$ regularized solution is found as $\hat{x} = P\hat{a}$, where

$$\hat{a} = \arg \min_a \|y - APa\|_2^2 + \tau \|a\|_1 \quad (2)$$

The solution to Eq. (2) provides estimates of reflectance spectra more accurate than conventional methods like Wiener filtering⁸. We used sparse recovery methods^{18,19} for finding estimates of multispectral images.

5. VALIDATION

Figure 6 shows an example of results from using the sparse recovery method on LED illuminator data.

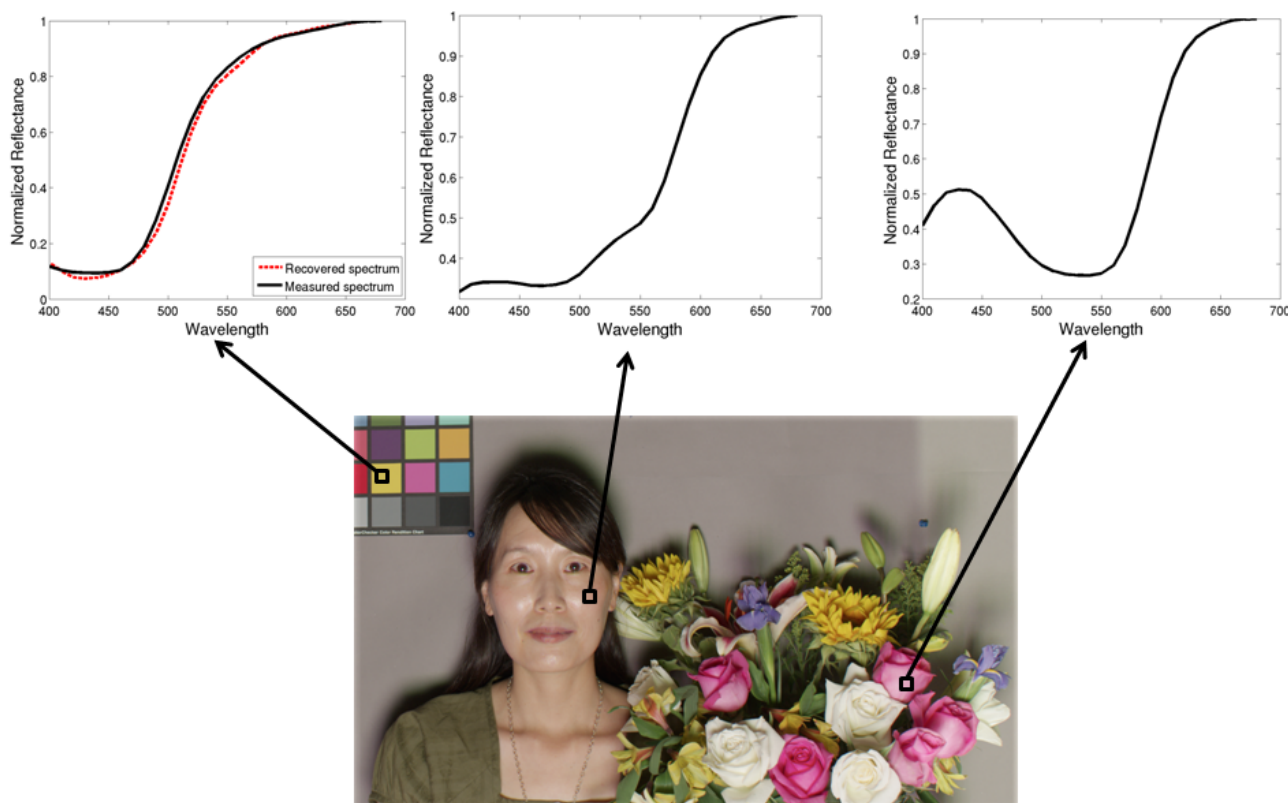


Figure 6. Top panels – estimated reflectance spectra from 3 different regions of the multispectral scene (indicated by black rectangles). Top left panel shows a comparison of estimated and measured reflectance spectra of an MCC patch. Bottom panel – sRGB rendering from estimates of reflectance spectra found with the LED imaging system.

The bottom panel shows an sRGB rendering of a multispectral scene. The top 3 panels show plots of the average reflectance spectra from areas in the image indicated with black rectangles. The top left panel shows a comparison of estimated reflectance of a patch from the MCC plotted along with a measurement of the same patch. Note the close correspondence between measured and estimated reflectance spectra.

A similar comparison is shown for a patch of skin in Figure 7. The left panel shows an sRGB rendering of the multispectral scene. The right panel shows a comparison of the estimated spectrum of an area in a scene along with the measured spectrum of the same area.

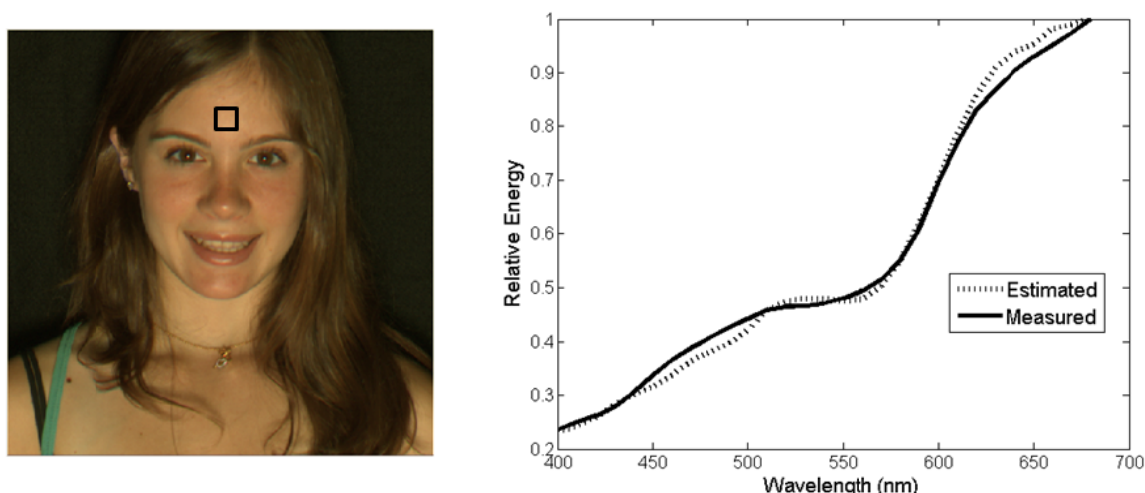


Figure 7. The spectral image of a female face is rendered by summing the energy in long-, middle- and short-visible wavebands and assigning these to the R, G and B primaries, respectively. The graph compares the measured and estimated spectral reflectance of a region selected from her forehead (demarcated with a rectangle).

6. DISCUSSION

Many researchers have used methods based on optical filters to acquire multispectral images of artwork^{2, 3, 6, 9}, objects and calibration targets¹⁰, scenes with IR energy⁷, and natural scenes¹¹⁻¹³. Since a number of acquisitions are required with different optical filters, these methods are best suited for imaging static scenes. Long exposure times preclude their use method for acquiring scenes that include people and other dynamic objects. The time required to change filters may be reduced by the use of filters mounted on a color wheel, but this renders the device physically cumbersome and expensive.

An alternate approach is to use multiple acquisitions of a scene illuminated by lights with different spectral power distributions. Since lighting systems may be designed to switch at high rates, this approach can be used to acquire multispectral scenes with people and other animate objects. We have created a system that uses multiple LEDs for capturing multispectral scenes. The multispectral scene data can be freely downloaded from the internet²⁰. Examples of the scene content are shown in Figure 8.



Figure 8. Thumbnail representations of three multispectral scenes that can be freely downloaded from the internet²⁰.

It is possible to use the led lighting system to capture multispectral video sequences as well. We demonstrated this capability by coupling the LED-based lighting system to a Micron MT9P031 video imaging sensor. The LED switching times are synchronized with the frame acquisition of the imager such that we can acquire multispectral video sequences with VGA resolution at approximately 10 fps. Higher frame rates may be achieved by reducing the spatial resolution.

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