

# TOWARDS MULTISPECTRAL DATA ACQUISITION WITH HAND-HELD DEVICES

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## ABSTRACT

We propose a method to acquire multispectral data with hand-held devices with front-mounted RGB cameras. We propose to use the display of the device as an illuminant while the camera captures images illuminated by the red, green and blue primaries of the display. Three illuminants and three response functions of the camera lead to nine response values which are used for reflectance estimation. Results are promising and show that the accuracy of the spectral reconstruction improves in the range from 30-40% over the spectral reconstruction based on a single illuminant. Furthermore, we propose to compute sensor-illuminant aware linear basis by discarding the part of the reflectances that falls in the sensor-illuminant null-space. We show experimentally that optimizing reflectance estimation on these new basis functions decreases the RMSE significantly over basis functions that are independent to sensor-illuminant. We conclude that, multispectral data acquisition is potentially possible with consumer hand-held devices such as tablets, mobiles, and laptops, opening up applications which are currently considered to be unrealistic.

**Index Terms**— Multispectral, mobile devices, color measurements

## 1. INTRODUCTION

For many applications CIE tri-value description of color, as is provided by for example  $XYZ$  or  $L^*a^*b^*$  values, is not sufficient and a multispectral description is desired. These applications vary from consumer products, such as paint selection, online cloth shopping, cosmetics industry and to more specialized fields such as in eHeritage and fruit quality assessment. For all these applications multispectral acquisition of color allows users to disentangle the set of metamers (different multispectral reflectances which map to the same tri-value), and provides a more precise description of color.

There exist two main approaches to multispectral data acquisition. The first method, and by far the most popular, is



**Fig. 1.** Multispectral data can be obtained with hand-held devices by using the screen to illuminate the object under various illuminations. The acquired measurements can be used to reconstruct the spectral reflectance.

based on passing the light through filters which pass only part of the light. A variety of such multispectral cameras exist in the market, and they have as main advantage that they are very accurate. However, because this type of multispectral camera is expensive, it is only available to specialized laboratories. A second approach to multispectral imaging is based on the duality which exists between changing the filters in front of the camera and changing the illuminants of the scene [1, 2]. Park et al. [2] show that it is possible to obtain multispectral information from a camera by varying the illuminant. Furthermore, they experimentally show that in a controlled environment it is possible to obtain multispectral information with a RGB camera. The main advantage of this method is that one does no longer require a multispectral camera (or chromatic filter set) to obtain multispectral images. The main drawback of this method is that various illuminants have to be available to illuminate the scene. Because of this drawback this approach to multispectral imaging has attracted relatively little attention. In another recent work [3], the authors explore the prospect of commonly available lighting conditions to recover spectral reflectance. However, this method requires a calibration step because even for the illuminants of same family (i.e incandescent or fluorescent) the color temperature and spectral properties can vary significantly.

In this paper, we propose to use the screen of the hand-held devices to display a set of illuminants which can then be observed by a front-mounted camera. In Figure 1 an il-

illustration of the proposed approach is given. The object with unknown reflectance is held in front of the camera. At the same time that the camera captures images of the object the display depicts different colors, and thereby changes the illumination of the object. This process results in a set of acquisitions of the reflectance under varying illuminants. The output of the system will be a multispectral signature of the object estimated from these measurements. The main originality of our approach lies in the functionality shift where we use the display of the device as an illumination source. Previously, in a related work, [4] proposed a method to use a scanner as a colorimeter. Our work has a similar philosophy with a more challenging application. The observation that for many hand-held devices cameras are mounted alongside a display makes this an especially convenient solution. This is also true for laptops with a built-in webcam. Note that this solves the main drawback of earlier work [2, 1] which was the availability of multiple illuminants.

For the spectral reconstruction we propose an improvement on the method of Park et al. [2]. They use the observation that real-world reflectances can be well-approximated with a low-parameter linear model [5]. The basis functions for this low-parameter model are typically derived from the spectra of the Munsell color chips. In this paper, we use basis functions that discard the part of the Munsell reflectances that falls in the sensor-illuminant null-space.

## 2. MULTISPECTRAL DATA ACQUISITION FROM MULTIPLE ILLUMINATION

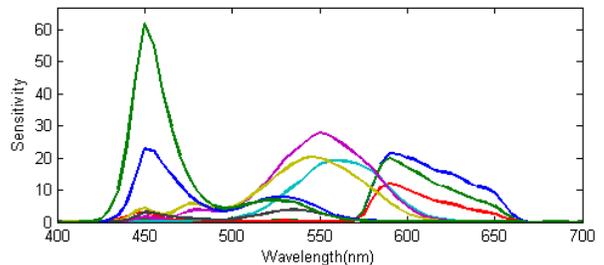
In this section we outline how to obtain multispectral data from multiple RGB measurements taken under various illuminants. Image formation in a camera can be modeled as

$$\rho_{mn} = \Gamma \left( \int_{\lambda} r(\lambda) c_m(\lambda) s_n(\lambda) d\lambda \right) + \epsilon_m \quad (1)$$

where,  $\rho_{mn}$  is the response of the camera.  $\Gamma$  is the camera non-linearity,  $r(\lambda)$  is the reflectance of a point in the object,  $c_m(\lambda) : m = 1 \dots M$  is the spectral sensitivity of the  $m$ -th channel of the camera,  $M$  being the total number of sensors and  $s_n(\lambda) : n = 1 \dots N$  is the spectral power distribution (SPD) of the scene illumination,  $N$  being the total number of illuminations. Finally,  $\epsilon_m$  is the noise of the  $m$ -th channel of the camera.

The main challenge is to reconstruct the reflectance  $r(\lambda)$  of the object from these  $MN$  measurements obtained from the camera. If we consider the spectra as discrete signals and by merging the illuminations and the camera sensors into one matrix  $P$  whose each column is the product between one sensor sensitivity and one illuminant SPD, Eq. 1 can be rewritten in matrix form as :

$$\rho = \Gamma (r^T P) + \epsilon \quad (2)$$



**Fig. 2.** Nine sensor-illuminant pairs resulted from RGB sensors of Sigma SD-10 camera and RGB primaries of a DELL E4310 laptop.

where  $\rho$  is the response of all the sensor-illumination pairs given the reflectance  $r$ . Estimating  $r$  from Equation 2 leads to an ill posed problem, thus additional constraints are needed to solve the problem.

There are two notable works under similar setup. Park et al. [2] use a led-based customized illumination system. They use this system to facilitate fast capture of multispectral data. To reconstruct the reflectance, they propose to minimize a regularized constrained optimization problem. They project the sensor-illumination pairs in a low parameter orthogonal basis function space and optimize basis vector coefficients to minimize the  $L2$ -norm in the measurement space. Chi et al. [1] propose to place the filters in front of the light source (instead of the lens) to generate multiple illumination, they run an expensive algorithm to select appropriate set filters from a very large set and use direct pseudo inverse [6] to learn a mapping from camera measurement space to reflectance space. They choose this approach to eliminate the effect of ambient light.

Differing from existing methods, where the illuminants are chosen to optimize spectral resolution, we propose to use the screen of hand-held devices as the changing illuminant of the scene. As the illuminants we use the three primaries of the screen in isolation, giving a red, green and a blue illuminant. In the case of a RGB camera we therefore have a total of nine measurements: the three camera channels for each of the three illuminants. Sensor-illumination pairs obtained from a camera and screen primaries are displayed in Fig. 2.

## 3. REFLECTANCE ESTIMATION WITH SENSOR-SENSITIVE BASIS FUNCTIONS

In this section we explain the reflectance estimation method of Park et al. [2] in more detail and propose a way to improve this method. Their method constraints the reflectance estimation problem by noting that the spectra of real-world reflectance can be well approximated by a low-parameter linear model [5]. This linear model is independent of the sensor system. Here, we investigate adapting the linear model to the sensors to achieve improved reflectance reconstruction.

Park et al. [2] approximate the reflectance of real-world materials with a limited number of spectral basis functions according to:

$$r(\lambda) \approx \sum_{k=1}^K \sigma_k b_k(\lambda) \quad (3)$$

where  $\sigma_k$  are scalar coefficients of the  $K$  basis functions  $B$  ( $B = b_k(\lambda)$ ). These basis functions can be computed with eigenvector analysis (PCA) of the 1257 Munsell color chips [5].

Since their approach is independent of the sensor-illuminant sensitivities  $P$ , there is no reason that the resulted basis functions are the best to reconstruct multispectral data from the given sensor-illuminant pairs. Thus, we propose to adapt the spectral basis to the sensor-illuminant spectra. Considering the reflectance of the Munsell data set  $R$  ( $k \times l$  matrix, with  $k$  Munsell chips which are described by a  $l$  dimensional spectra), we propose to break the Munsell data set in two parts:

$$R = R^P + R^{\perp P}, \quad (4)$$

where  $R^P$  is the part of the spectra which is in the illuminant-sensor space and  $R^{\perp P}$  is the part of the Munsell spectra which is perpendicular or in the null-space to the sensor-illuminant space [7] and for that reason cannot be observed. The matrix  $R^P$  can be computed with:

$$R^P = RP(RP)^+, \quad (5)$$

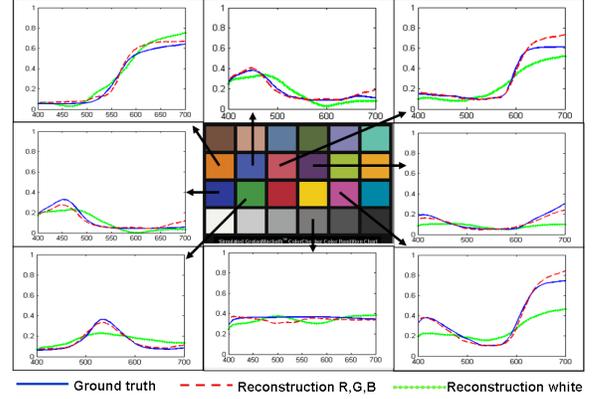
where  $(RP)^+$  is the Moore-Penrose pseudo inverse. Then we propose to apply a PCA on the  $R^P$  reflectances rather than on the original  $R$  reflectances. By this way, the resulted basis functions are not disturbed by information that is not visible from the acquisition device given the sensor-illumination sensitivities. We denote these sensor-illuminant aware basis functions as  $B'$ . Finally, in order to estimate the spectral reflectances from the camera responses  $I$ , we minimize the following objective function as suggested by Park et al. [2]:

$$\min_{\sigma} \left( |P^T B' \sigma - I|^2 + \alpha \left| \frac{\delta^2 r(\lambda)}{\delta \lambda^2} \right|^2 \right) \text{ subject to: } B' \sigma \geq 0 \quad (6)$$

where  $\alpha$  is the smoothness parameter and  $\frac{\delta^2 r(\lambda)}{\delta \lambda^2}$  is the smoothness constraint. This constraint helps to obtain reasonable solution if the matrix  $P^T B'$  is ill-conditioned. It is based on the observation that natural reflectances tend to be smooth. The positivity constraint  $B' \sigma \geq 0$  ensures that the reconstructed reflectance would not have negative values. For further details on this method, please refer to [2].

## 4. EXPERIMENTS

In this section, we present experimental results on both synthetic data and real camera output. In each case, we compare the improvement of the estimation accuracy when using three



**Fig. 3.** Comparative spectral estimation between R,G,B and white illuminants.

i.e. R,G and B display illuminants over white i.e.  $R+G+B$  (the sum of the three display primaries). We also compare our method with [2]. We use two different metrics for the comparisons, namely, RMSE and CIEDE00 color difference [8].

### 4.1. Experimental Setup

In our experiments, a DELL Latitude E4310 laptop (13.3 inch screen size) is used as illuminant. LCD display technology is most commonly used in all the hand-held devices and laptops likewise. For capturing the image, we use the Sigma SD-10 camera which allows storing images in RAW format. We use a separate camera and not a camera mounted on a hand-held device because RAW shooting is still rare in hand-held devices available now, but considering the boom in the tablet computers and the mobile phone industry, we believe this to be common within a few years time. Like several other methods e.g. [2, 9], our proposed modification, requires the knowledge of sensor-illuminant sensitivities which could be obtained from the manufacturer in an ideal situation. In our case, we measure the laptop SPDs using a Konica Minolta CS-1000a spectroradiometer. The camera response curve for the sigma SD-10 camera was obtained from [10]. Moreover, for synthetic experiments, we use an additional camera sensor response curve of a retina scientific camera to show the robustness of our method for different sensors.

### 4.2. Synthetic Data

In this section, we use the laptop display illuminant and two camera response curves. The Munsell color book spectra obtained from [11] is used for training as needed and two Gretag Macbeth ColorCheckers of 24 and 240 colors are used for testing.

Table 1 shows the theoretical limit of the estimation performance for the given sensor-illuminant pair. We can see from the table that, for each algorithm, color checker and

Experimental results for Display Illuminant and Sigma SD-10 Camera								
Method	ColorChecker 24				ColorChecker 240			
	White		R,G,B		White		R,G,B	
	RMSE	CIEDE00	RMSE	CIEDE00	RMSE	CIEDE00	RMSE	CIEDE00
Park [2]	0.044	2.22	0.023	0.43	0.032	2.99	0.016	0.42
Our Method	0.042	0.91	0.014	0.29	0.025	0.98	0.010	0.34
Experimental results for Display Illuminant and Retiga Camera								
Park [2]	0.043	3.71	0.023	0.57	0.031	3.25	0.017	0.52
Our Method	0.039	2.26	0.010	0.31	0.024	1.89	0.008	0.32

**Table 1.** Comparison of reflectance estimation accuracy between R,G,B and white illuminants for [2] and the proposed modification.

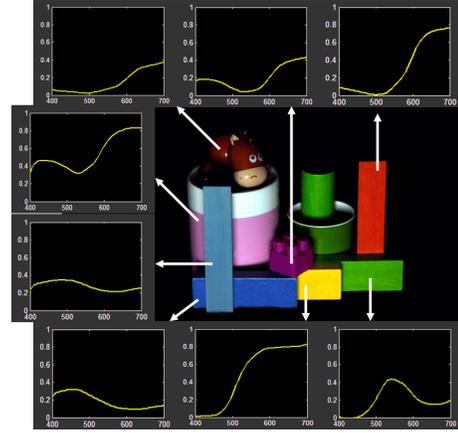
sensor-illuminant pair, the overall accuracy improves significantly when R,G,B primaries of the screen is used over the white (R+G+B). This significant improvement validates that multispectral acquisition using hand-held device is a worthwhile proposition. It is also clear that the proposed method clearly outperforms [2] in each case. These results confirm that sensor sensitive basis functions are relevant for accurate spectral reconstruction.

### 4.3. Real Camera Output

Here, we experimentally verify the accuracy of multispectral measurements which are obtained by illuminating materials with the primaries of a hand-held device.

**Image acquisition:** In this section, we use only the 24 patch color checker for reconstruction. As a rule of thumb, we hold the device orthogonal with the line that connects the plane of the display screen and the object plane. The distance between the device and the object is set to be approximately three-times the screen size. We assume that the camera and the scene are static. The effect of ambient light in reconstruction was not taken into account for this work, so the images are captured in a dark room with minimal ambient light. Ambient light could be taken into account as is shown in [1]. The comparison procedure followed is identical to that of the previous section. So, we capture 4 images of the color checker illuminated by R,G,B and the white(R+G+B).

**Results:** Table 2 shows the performance gain if three display primaries are used as illuminants over just one single light. For both the methods, the gain over white light is significant. The average RMSE gain on 24 patches varies from 30% for Park [2] to 40% for our method. CIEDE00 color difference is also improved significantly in each case. Moreover, our method outperforms [2] when R,G,B illuminants are used. Figure 3 shows estimation results for some spectra of the color checker. It is evident that the use of various illumination helps to improve the spectral resolution and better estimate the sharp changes in the reflectances than the white light which provides a poor spectral resolution. As a further illustration of our method can be used to estimate the spectral reflectances of every pixel of a scene, which then can be used for relighting or color constancy. Figure 4 shows an example with several estimated reflectances spectra.



**Fig. 4.** Spectral reflectance obtained by our method for several individual objects.

Method	White		R,G,B	
	RMSE	CIEDE00	RMSE	CIEDE00
Park [2]	0.063	7.4	0.043	2.62
Our Method	0.062	7.4	0.037	2.47

**Table 2.** Reflectance estimation performance comparison between R,G,B and white illuminants for [2] and the proposed method

## 5. CONCLUSION

We proposed a method which allows owners of hand-held devices with front-mounted RGB cameras to acquire multi-spectral data. Experiments show that potentially multi-spectral data acquisition with hand-held devices can significantly improve compared to taking a single color measurement under a known white light. In addition, our proposed algorithm improve reconstruction results on CIEDE00 scores up to 60%. However, current experiments did not include ambient illumination. Considering measurements in the presence of ambient light is one of the future direction.

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