Multispectral imaging using LED illumination and an RGB camera

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Abstract

LED illumination based multispectral imaging is getting much attention in recent years due to its fast computer controlled switching ability, availability of many different LEDs, robustness, and cost effectiveness. In this paper, we propose a system which uses an RGB camera along with two or three combinations of three different types of LEDs in order to acquire multispectral images of six or nine channels. Optimal LED combinations are selected so as to produce accurate estimate of spectral reflectance and/or color. The system is rather simple to realize. Moreover, it is faster as it requires only two or three shots, unlike state of the art multiplexed LED illumination based systems which require as many shots as the number of channels that a system can acquire. The proposed system can be useful in general multispectral imaging applications. The system has been evaluated with both the natural images and paintings. The results from the simulation experiments were promising, indicating the possibility of the proposed system as a practical and feasible method of multispectral imaging.

Introduction

Multispectral imaging has many advantages over traditional three channel (usually RGB) color imaging. It is less prone to metamerism, produces higher color accuracy, and unlike digital cameras, it is not limited to the visual range, rather can also be used in near infrared, infrared and ultraviolet spectrum as well, depending on the sensor responsivity range. Spectral reflectance of a scene which represents the unique property of an object, can be recovered from the images acquired with the spectral imaging systems. Multispectral imaging, therefore, has widespread application domains, such as remote sensing [1], astronomy [2], medical imaging [3], biometrics [4], culture and heritage [5, 6] and many others.

Many different types of multispectral imaging techniques and systems have been proposed in the literature. In a typical filter-based imaging system, either a set of traditional optical filters in a filter wheel, or a tunable filter [7, 8], or in front of a high quality digital camera [9–11] or a stereo camera [12, 13] are employed. Multispectral filter array (MSFA) [14–17] is another type of multispectral imaging technique which extends the filter array from 3-channel like in Bayer pattern further, allowing to capture more than 3 bands.

Another promising technique of multispectral imaging, which is of our primary interest in this paper, is based on a multiplexed LED (Light Emitting Diode) illumination [18–20]. In a typical LED illumination based multispectral imaging system, a set of n different types of LEDs are selected, each type of LED is illuminated in a sequence, and a monochrome camera captures an image under the illuminated LED, thus producing a n band multispectral image. Such a system modulates the illumination and provides a multispectral light source. LED illumination based multispectral imaging has been used in several applications like biometrics [4], medical imaging [3] and film scanner [21]. This has got much attention in recent years because of the advantages of the LEDs: fast computer controlled switching ability, robustness, and cost effectiveness. Availability of many different color and high intensity LEDs with peak weavelengths spanning the whole visual range and even infrared region has made the construction of more effective multispectral system possible. Shrestha et al. [21] recently proposed a LED based spectral film scanner. Tominaga and Horiuchi [20] proposed multispectral imaging by synchronizing capture and illumination using programmable LED light sources. Studies are being done to anayze and address different issues with the LED based multispectral imaging. Spectral variability of LEDs with angle and time of usage is one example of such studies, done by Martinez at al. [22]. They found that white light LEDs designed with a blue emitting LED coated with a yellow emitting phosphor, emit light whose spectrum changes as a function of the angle and time. On the other hand most of the single color LEDs are found to be invariant compared to the white lights, and hence they are recommended to be used in LED based multispectral systems. Shrestha and Hardeberg [23] has proposed a binary tree based LED matrix/panel design method which produces an optimal or suboptimal arrangement of LEDs for equal energy and uniform ligthing in a LED based multispectral imaging system.

Most of the state of the art LED based multispectral imaging systems require many different LEDs and many shots (n shots for n types of LED) in order to acquire a multispectral image of a scene, and this also makes the systems complex, limiting their practicability and feasibility. In this paper, we propose an efficient LED illumination based multispectral imaging system that requires fewer shots, using an RGB camera. Instead of lighting a LED at a time sequentially, combinations of three optimal LEDs are selected, each combination of LEDs is lit at a time, and a three band image is captured by the camera each time. With n shots, we can acquire $3n$ band multispectral images. The system is practical, and easily and cheaply realizable. It can be used as a general multispectral imaging system in many different applications including in culture and heritage artworks. We present the results with the natural images, and painting images using a famous painting, the Scream, by Edvard Munch from 1893 as an example.

After this section, we present next the proposed system and the methodology. We then present experiments and results. The results will be discussed next, and finally we conclude the paper.

The system and methodology

The proposed LED illumination based multispectral imaging system comprises of an RGB camera, LED panel(s) and a microprocessor based controller (or a computer), as illustrated in Figure 1. A LED panel is built with combinations of three different types of LEDs, or alternatively, more than one LED panel, with each panel comprise of three types of LEDs can be used. We assume that the LED panel is made in such a way that the resulting illuminat m.

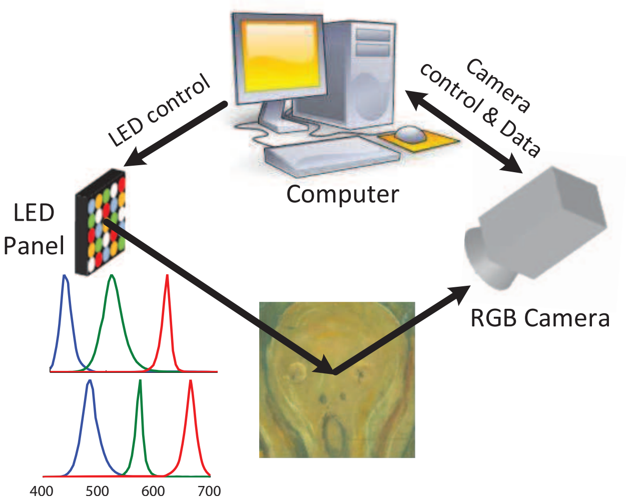


Figure 1. *Illustration of the proposed system*

The LED combinations are selected such that each LED in a 3-LED combination splits one of the three spectral sensitivities of the camera in a different region so as to allow the system to capture an image effectively in different spectral bands (wavelengths) along the visual range of the spectrum. Many different types of LEDs whose wavelengths more or less cover the whole visual range of the spectrum are now available in the market. Such a set of LEDs can be used in order to select optimal combinations of LEDs. The set is divided into three groups based on their peak wavelengths lying in the blue, the green, or the red regions of the sensitivities of the camera used to build the system. A 3-LED combination is lit and image of a scene is captured with the camera, under the resulting illumination. This gives a 3-band image. n such different 3-LED combinations give $3 \times n$ camera responses. These camera responses correspond to a $3 \times n$-band multispectral image, captured through the modulated light, theoretically, in $3 \times n$ different wavelengths. Spectral reflectance of the scene is then estimated from these $3 \times n$ camera responses, using an appropriate spectral estimation method. We present this in details along with the system model in *System Model* subsection below.

Optimal selection of 3-LED combinations can be done through exhaustive search based on accuracy of the spectral and/or color reproduction, depending on the application requirement. The exhaustive search method is computationally expensive as it checks every possible combination. However, by limiting the number of LEDs in the given set, and also the value of n to say 3, the search space can be kept computationally tractable. Moreover, repetitions of the LEDs can be avoided while searching for the different combinations.

System model

Each shot in a n-shot system produces 3-band image corresponding to the three camera sensitivities. Let $S = [s^R, s^G, s^B]$ be the matrix of spectral sensitivities of the three channels of the camera, and l_i^R, l_i^G and l_i^B denote the spectral power distributions (SPD) of the 3 LEDs from the red, green and blue regions respectively, in the i^{th} LED combination; $i = 1 \dots n$. Then, the spectral power distribution of the resulting illumination is given by $L_i = \text{sum}(l_i^R, l_i^G, l_i^B)$. Let R be the spectral reflectance of the surface captured by the camera, then the camera responses $C_i = [c_i^R, c_i^G, c_i^B]'$ are given by:

$$C_i = S\text{diag}(L_i)R + \eta_i; \qquad i = 1 \dots n \tag{1}$$

where η_i is the acquisition noise. C' denotes transpose of the matrix C. The combined $3 \times n$ responses are then given by $C = [C_1', \dots, C_n']'$.

The estimated reflectance ($\tilde{R}$) is obtained for the corresponding original reflectance (R) from these camera responses, using an appropriate spectral estimation method. We use a simple linear regression method here in this paper. Let C_{train} and C be the camera responses of the training and the test targets respectively. Then the estimated reflectance is given by:

$$\tilde{R} = R_{\text{train}} C_{\text{train}}^{+} C \tag{2}$$

The performance of the system can be evaluated by the accuracies of the estimated spectral and/or colorimetric values. For this, the most commonly used RMS (Root Mean Square) error has been used as the spectral metric, and the ΔE_{ab}^* (CIELab color difference) as the colorimetric metric.

Experiments

In this section, we discuss the experimental setup, and then present experiments and results obtained. All the experiments are carried out through simulations.

Experimental setup

The experimental setup comprises of spectral data of a camera, LEDs, surface reflectances of the training surfaces, and the test hyper-spectral images. A Canon 20D camera whose spectral sensitivities shown in Figure 2 is used.

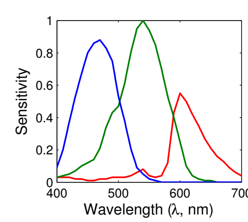


Figure 2. *Spectral sensitivities of the Canon 20D camera*

For the LED selection experiment, we used the same 35 LEDs used by Shrestha et al. in [21]. The spectral power distributions of these LEDs were measured from the real LEDs from the market. Among the 35 LEDs, there are several LEDs that have the same or almost the same peak wavelengths and the shape. In order to make the exhaustive filter selection feasible, such similar LEDs are skipped, keeping the LEDs that cover the visible range more or less uniformly. We selected 19 LEDs from the 35, and they are ultimately used in the selection of the LEDs for building the proposed multispectral imaging system. Spectral power distributions of these LEDs are shown in Figure 3. The individual LEDs are numbered for identification.

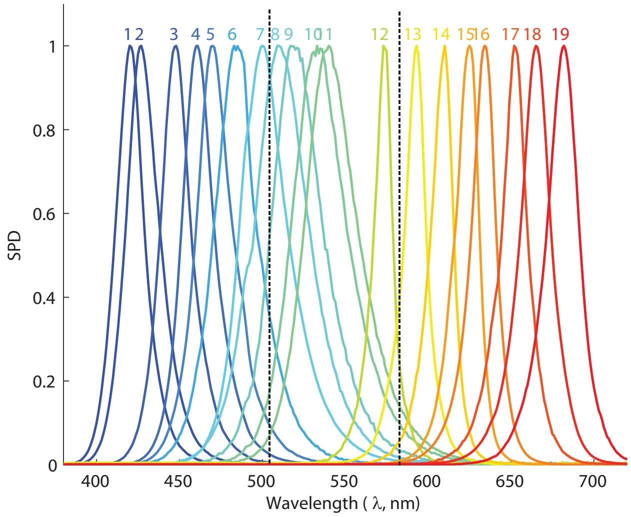


Figure 3. *Normalized spectral power distributions of the 19 LEDs used*

In order to evaluate the performance of the system, hyperspectral images have been used to acquire simulated images, and also as references. The evaluation is done for natural scenes as well as for paintings. For this, eight natural scenes from Nascimento et al. [8] have been used. Figure 4 shows the RGB images generated from these hyperspectral images under D65 illuminant. For the painting, we have acquired calibrated hyperspectral images of a famous painting by Edvard Munch from 1893, the Scream, in the National Museum of Norway, using a hyperspectral camera, HySpex-VNIR 1600 from Norsk Elecktro Optikk. The hyperspectral image has 160 spectral bands from 415nm to 990nm in 3.6nm resolution. However, we used the data in the visual range (414nm-700nm) only. Since the size of the whole image is quite large, we used the three interesting regions of the whole painting. These regions are shown in Figure 5. We used the central 300×300 block of the images, in order to lower computation time.

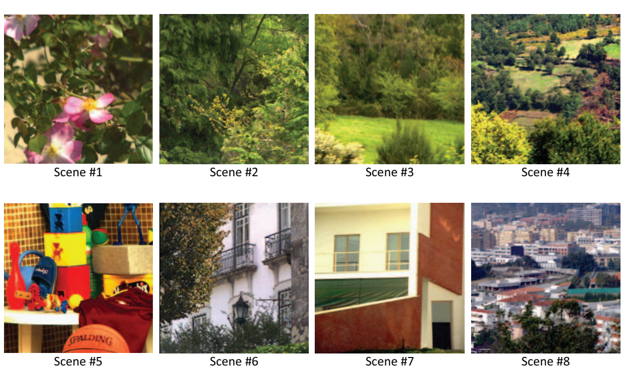


Figure 4. *RGB images of the 8 natural scenes from Nascimento et al. [8]*

Surface reflectance of the 240 patches of the Macbeth color checker DC (MCCDC) is used for the training, and also for testing in the optimal LED selection. Sixty-three patches of the MCCDC have been used as the training dataset; and one hundred and twenty-two patches remained after omitting the outer surrounding

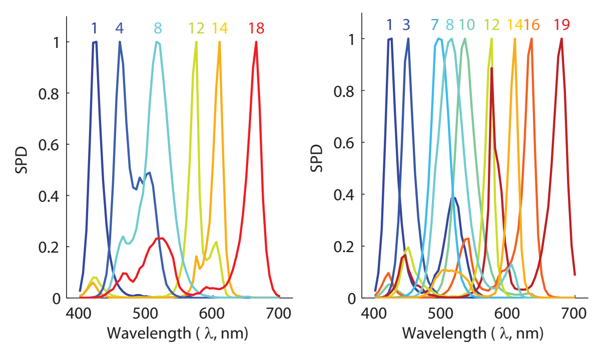
(a) Region #1 (b) Region #2 (c) Region #3

Figure 5. *RGB images of the 3 test regions of the Scream painting*

achromatic patches, multiple white patches at the center, and the glossy patches in the S-column of the DC chart have been used as the test dataset in the spectral reflectance estimation. The training patches have been selected using linear distance minimization method (LDMM) proposed by Pellegri et al. [24].

Experiments and results

The whole experiment comprises of two parts. The first part of the experiment is the selection of LEDs. The set of 19 LEDs is divided into three groups: 1-7 in the blue region, 8-12 in the green region, and 13-19 in the red region. These regions are shown in the Figure 3 separated by two dotted lines. The division is done based on the crossings of the spectral sensitivity curves of the three channels of the camera. Optimal combinations of 3 LEDs, one each from these three groups are selected through exhaustive search as presented above. Using the training and the test targets from the MCCDC, estimated spectral reflectance of the test patches are obtained using the linear regression based spectral estimation method (Equation 2). A set of LED combination(s) that produces the minimum RMS error is considered as optimal. The normalized channel sensitivities (combination of the LEDs and camera sensitivities) of the resulting 6 and 9 band multispectral imaging systems from the 2-shot and 3-shot versions are shown in Figures 6(a) and 6(b) respectively.



(a) 6-band system (b) 9-band system

Figure 6. *Normalized channel sensitivities of the resulting 6 and 9-band multispectral systems. The numbers above the spectra identify different LEDs.*

From the selected LED combinations, we see that the peaks of the resulting channel sensitivities are reasonably well spaced covering more or less the whole visual range. This makes the system capable of capturing reasonably good information throughout the visual range.

The next part of the experiment simulates the proposed multispectral imaging system built from the Canon 20D camera and the LED combinations selected by the LED selection algorithm. The simulated camera responses acquired under the selected LED combinations are obtained from the hyperspectral images of the 8 natural scenes and the 3 regions of the Scream painting. The three camera responses in each pixel from each shot are obtained through bilinear demosaicking. The process of bilinear interpolation has been well described by Baone and Qi [14]. In order to make the simulations more realistic, simulated random shot noise and quantization noise are introduced in the camera responses. Barnard et al. [25] investigated the noise in trichromatic cameras and came to a conclusion that a realistic level of shot noise in a trichromatic camera is between 1% and 2%. Therefore, the maximum 2% normally distributed Gaussian noise is introduced as a random shot noise. 12-bit quantization noise is also introduced by directly quantizing the simulated responses after the application of the shot noise.

The spectral reflectances of a scene are estimated from the camera responses using the linear regression method as presented above in the *System Model* section, using the MCCDC training dataset as the training target. The two metric values RMS and ΔE^*_{ab} are calculated using the estimated spectral reflectance and the measured spectral reflectance from the hyperspectral images. The mean of the metric values obtained from the natural and the painting images, along with the standard deviations are given in Table 1. For comparative analysis, the results produced by the 3-channel RGB camera, and two state of the art multiplexed LED illumination based multispectral imaging systems which use a monochrome camera, and the same number of LEDs as in the proposed system (6 and 9), are also given. The optimal LEDs for these systems are selected also through exhaustive search from the set of 19 LEDs, using the same optimization criteria. The table also shows the LEDs selected by the LED selection algorithm, for the later four types of systems.

Table 1: Mean spectral and color estimation errors for the natural and painting images

System	LEDs	Image	RMS		ΔE^*_{ab}	
			Mean	Std	Mean	Std
RGB + D65		Natural	0.033	0.019	3.357	2.234
		Painting	0.020	0.007	3.775	1.971
		Average	**0.027**	**0.013**	**3.566**	**2.103**
Mono + 6 LEDs	1, 5, 9, 12, 14, 18	Natural	0.025	0.014	1.269	0.758
		Painting	0.008	0.002	1.684	0.725
		Average	**0.017**	**0.008**	**1.477**	**0.742**
Mono + 9 LEDs	1, 3, 6, 7, 10, 12, 14, 15, 19	Natural	0.020	0.010	0.970	0.502
		Painting	0.008	0.003	0.861	0.455
		Average	**0.014**	**0.006**	**0.915**	**0.479**
RGB + 2 x 3 LEDs	1 12 14	Natural	0.028	0.015	2.294	1.754
	4 8 18	Painting	0.013	0.005	2.621	1.706
		Average	**0.020**	**0.010**	**2.457**	**1.730**
RGB + 3 x 3 LEDs	1 10 16	Natural	0.025	0.014	1.996	1.570
	3 12 19	Painting	0.015	0.007	2.358	1.539
	7 8 14	**Average**	**0.020**	**0.011**	**2.177**	**1.554**

The results show that the state of the art multiplexed LED illumination based 6-band system with the monochrome camera produces the average (of natural and painting images) RMS and ΔE^*_{ab} values of 0.017 and 1.48 respectively. The performance is improved slightly with the 9-band system, though not significantly. The proposed system with 6-bands (RGB + 2×3 LEDs) produces the average RMS and ΔE^*_{ab} values of 0.02 and 2.46 respectively. The 9-band system (RGB + 3×3 LEDs) produces the corresponding metric values of 0.02 and 2.18, not so significant improvement from the 6-band system. The performance of the 3-channel RGB camera, as expected, performs the worst both in terms of the spectral and the colorimetric reproductions. We discuss more on the results in the next section.

To illustrate the results, the estimated and the measured spectral reflectances at the two manually selected pixel locations on the eight natural images, as obtained with the 6-band multispectral system are shown in Figure 7. Similarly, Figure 8 shows the spectra at the four different, randomly picked pixel locations on the three image regions of the Scream painting. We see that the estimated spectral reflectances are reasonably close to the measured ones with the natural, and the results of the estimation is even better with the painting images.

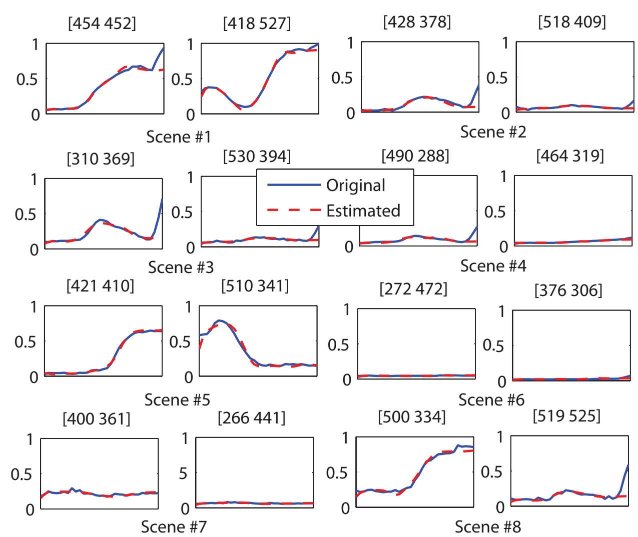


Figure 7. *Reflectance spectra at the two different pixels in the eight natural images. The pixel locations are shown above the plots.*

Discussion

From the experimental results, we see that proposed system performs significantly better both spectrally and colorimetrically in the case of both 6-band and 9-band systems, compared to the traditional RGB camera. Plots of the estimated and measured spectral reflectance also show very good estimation of the spectra. However, the performances of both the systems are slightly lower than the state of the art systems. This is not unexpected, because unlike the later ones, the proposed systems require demosaicking step and this introduces some spatial errors. This plays a big part in increasing the estimation errors. The objective behind the proposed system is to address the problems of the state of the arts systems and at the same time

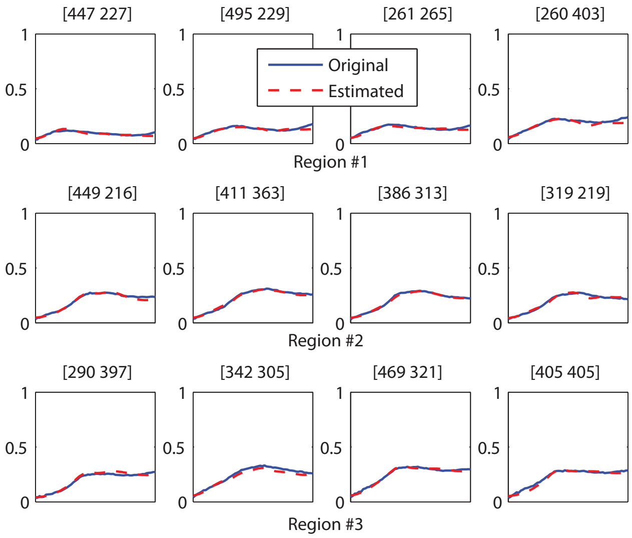


Figure 8. *Reflectance spectra at the four different pixels in the three regions of the Scream painting.*

try to keep the performance comparable and acceptable for many applications. We used a simple bilinear demosaicking algorithm in our experiments. Better results can be expected with a more sophisticated demosaicking algorithm.

The problems with the state of the art systems are that their design is relatively complex and need more shots to acquire an image. The proposed system is relatively much simpler and requires much less number of shots. On top of that the system can be realized cheaply. These advantages might outweigh the slight performance reduction, and make it a practical and feasible in many applications. We consider the performance of the proposed system (with ΔE^*_{ab} of less than 3 and RMS of less than 3%) as promising as it could be good enough in many applications, including the cultural and heritage area. Many museums still use high-end digital cameras and color management techniques to capture the artworks to achieve high quality images. The proposed system could be used instead to improve the results by providing information from more than 3 channels.

Several observations can be made from the experimental results. We can see that the performance is not improved with the 9-band compared to the 6-band system. The improvement is not so significant even in the case of monochrome camera based system. This shows that the increase in the number of bands not necessarily improve the system performance. This could be because of the influence of noise which becomes more prominent as the number of band grows.

Yet another observation we can make is that all the five systems perform relatively better with the painting images compared to the natural images, in terms of spectral estimation. This is because of the use of MCCDC as the training dataset as it represents more close to the spectra of the painting compared to the natural images. The performance may not perform that well in the case of images where spectral curves show strong swings. More study could be done as a part of the future work to see the behaviour in such cases. It is important to note that we should choose an appropriate training dataset which is close representative of the test data that will be used in an application.

Conclusion

The proposed LED illumination based multispectral imaging system can acquire multispectral images with a reasonably less number of shots, compared to the state of the art LED illumination based systems. It is practical and feasible, since the system can be built using an off-the-shelf digital camera and color LEDs that are available in the market. The results from the simulation experiments on both the natural and painting images show that the performance of the system is comparable to the state of the art systems. The system could be useful in many applications, for instance in the culture and heritage artworks. As a future work, it would be interesting to realize the system, and do experimental validation of the results from the simulation.

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