Spectral image reconstruction by a tunable LED illumination

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ABSTRACT

Spectral reflectance estimation of an object via low-dimensional snapshot requires both image acquisition and a post numerical estimation analysis. In this study, we set up a system incorporating a homemade cluster of LEDs with spectral modulation for scene illumination, and a multi-channel CCD to acquire multichannel images by means of fully digital process. Principal component analysis (PCA) and pseudo inverse transformation were used to reconstruct the spectral reflectance in a constrained training set, such as Munsell and Macbeth Color Checker. The average reflectance spectral RMS error from 34 patches of a standard color checker were 0.234. The purpose is to investigate the use of system in conjunction with the imaging analysis for industry or medical inspection in a fast and acceptable accuracy, where the approach was preliminary validated.

Keywords: principal component analysis, spectral reconstruction, LED illumination

1. INTRODUCTION

The color perception of an object varies under different situations. It is determined by three attributes: scene illuminants, spectral reflectance of the object and observers. In terms of color engineering, metamerism reveals a fundamental phenomenon that different reflectance spectrum can lead to the same color perception by human under specific conditions [1]. Reconstructing the spectral reflectance from image sensor outputs is essential not only for avoiding vision mistakes caused by metamerism, but also for more accurate material or industrial identification. Spectral imaging is a technique that combines spectroscopic system and imaging technique [2]. It requires to create a three-dimensional (3D) data cube involving a series of images of the same object, where each one of them is measured at different wavelengths. Generally, a dispersive element (or scanning setup) is needed when acquiring the spectral information in time domain or spectral domain or spatial domain sequence. Optical elements such as color filter wheel, liquid crystal tunable filter, acousto-optic filter, prism, and gratings are employed. Despite scanning process can be quite precise, these approaches sometimes face challenge with its inherent bulky optomechanical setup and low speed.

Multispectral imaging is widely used in fields such as remote sensing, artwork reproduction, medical diagnosis and so on. Most of the multispectral imaging technique use filters and monochrome charge-coupled device (CCD) to produce different channels of digital counts [3]. However, there exists mechanical difficulties and other obstacles in using filters. Instead of placing filters on the pathways of imaging, in this study, we offered active illuminants to produce different spectral channels. We setup a platform capable of acquiring images at least one order of magnitude more quickly than the existing tunable filter system. One superiority in this system lies in an active spectrally-tunable LED light source by our group [4][5]. By an optimal spectral mixing of LEDs with dynamic control, we can manipulate color channels at will. An integrating sphere was added to offer a stable and uniform lighting environment. In the following paragraph, we will introduce the platform layout and numerical algorithm in detail. Experimental results will be given to prove the feasibility of spectral reconstruction with multispectral imaging.

Imaging Spectrometry XVIII, edited by Pantazis Mouroulis, Thomas S. Pagano, Proc. of SPIE
Vol. 8870, 88700C · © 2013 SPIE · CCC code: 0277-786X/13/$18 · doi: 10.1117/12.2023263

2. MULTISPECTRAL IMAGING TECHNIQUE

2.1 Concept of multispectral imaging

Multispectral imaging is a fully digital technique that uses digital counts of imager to estimate the spectral reflectance of an object. Figure 1 is the flow chart of the multispectral imaging. First of all, a training database was selected in accordance with purpose and measuring the spectral reflectance of each data set. Munsell catalog in moderate colors were chosen as training target for general purpose of color inspection. Secondly, Principal Component Analysis (PCA) was employed to find out the eigenspectral components of the selected database [6]. In this study, merely six principal components were sufficient for reconstruction accuracy up to 98%, meaning that the first six eigenvectors is enough to extract the spectral feature of the selected spectral dataset (moderate color group). Certainly, the number of component is highly relevant to the spectral complexity. PCA helped us reduce data volume and shorten the processing time. As well, multichannel imager was used to acquire those color patches, accompanying with two pre-defined illuminations, six channels of digital counts could be retrieved. We could derive a transformation matrix to find the relationship between the digital values of each pixel and its spectral reflectance. In other words, talking about the calibration of the imaging system, we must characterize the entire imaging system to find the correspondence between the digital counts of imager and the illumination upon it. With the aid of the transformation matrix, there's no need to measure nor scan through the whole spectral domain. The spectral reflectance of interested target could be obtained simply by the measured digital values of the imager. Finally, the reconstruction can be conducted by the pseudo-inverse algorithm.

2.2 Spectral reconstruction equations

The transformation matrix, which links the correspondence of digital counts of imager and spectral estimation of each pixel, is the kernel of algorithm based on the camera model. Equation (1) represents that the digital counts of CCD with the k-th channel is determined by the integration of illuminant $l(\lambda)$, the k-th channel of CCD's sensitivity function $s_k(\lambda)$ and spectral reflectance $r(\lambda)$ of the object.

$$c_k = \int s_k(\lambda) l(\lambda) r(\lambda) d\lambda \tag{1}$$

We can reformulate it into a matrix form as equation (2):

$$C_k = S_k^{\mathrm{T}} Diag(L) R \tag{2}$$

Since the spectral sensitivity of CCD is unknown, we employed an indirect approach based on learning reconstruction. Instead of directly measurement of sensitivity functions of CCD, a set of color patches were used as the calibration targets in the training database. The results are greatly influenced by the calibration targets. In terms of camera model in equation (3), the digital counts and spectral reflectance of each color patch in the training database have been measured already. The M matrix is the transformation matrix between digital values and spectral reflectance. The idea of multispectral imaging is to retrieve the reflectance information from the camera response. If the noise could be neglected in a constrained environment, there exists an inverse linear operator, the so called transformation matrix, between digital values of imager C and corresponding spectral reflectance R.

$$\mathrm{C}_{\mathrm{train}} = \mathrm{MR}_{\mathrm{train}} \tag{3}$$

The transformation matrix M can be obtained via pseudo-inverse operation. The dimension of each matrix in equation (3) is the first thing to determine before applying pseudo inverse. Spectral reflectance of the patches based on Munsell color catalog, R, is a n*k matrix (n: wavelength intervals; k: number of color patches). C is the digital values, with dimension m*k (m: camera channel number). Namely, when $k \geq m$, the problem becomes a least square approximation, where M is the matrix which projects the spectra in dataset onto camera basis. We can derive matrix M as equation (4), and pinv stands for pseudo inverse.

$$M=C_{train}\,pinv(R_{train}) \tag{4}$$

Principal component analysis (PCA) is an effective approach to reduce the dimension of training dataset. We used PCA to extract the eigen-spectral components who dominate the spectral properties of the original dataset. E is the matrix where each column is an eigenvector of R_{train}, where A and $\bar{R}_{train}$ represent the weighting factors and mean spectrum, respectively. As we used eigen-spectral bases (R_{train}) in replace of original standard spectral bases (R_{train}),equation (3) can be expressed as equation (6):

$$R_{train}=EA+\bar{R}_{train} \tag{5}$$

$$C_{train}=QA+M\bar{R}_{train} \tag{6}$$

Where we use a new matrix Q = ME to simplify the expression. Once we obtain the correspondence between the digital counts and weighting factors, we can estimate an unknown sample (A_{test}) by transformation matrix based on the training dataset. In equation (7), the digital counts C_{test} is already known by imager. We aimed to find out the corresponding weighting factors A_{test} for the purpose of spectral reconstruction.

$$C_{test}=QA_{test}+M\bar{R}_{train} \tag{7}$$

In equation (8) we compute the weighting factors of test samples.

$$A_{test}=Q^{-1}C_{test\text{-}modified} \tag{8}$$

The last step is to put the weighting factors back into the eigen-spectral components of the system in interest, the spectral reflectance can be thus reconstructed from digital values of imager:

$$R_{test}=EA_{test}+\bar{R}_{train} \tag{9}$$

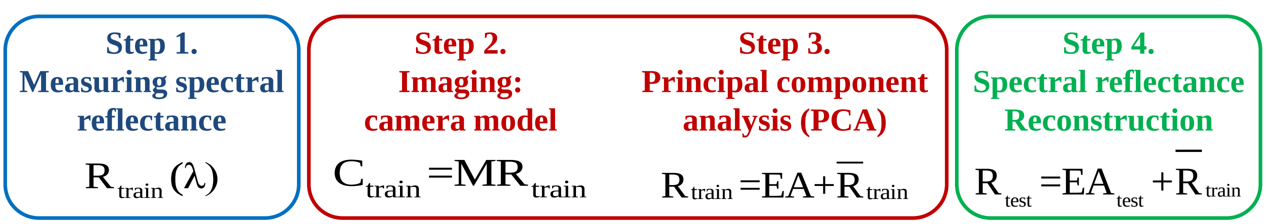

Figure 1 : We aimed to build the relationship between spectral reflectance and digital counts through multispectral imaging technique. The first step was to measure spectral reflectance of a set of chosen patches as our training database. Then imaging these color patches with our platform. Those measured spectral reflectance were analyzed with PCA. With these digital counts and spectral reflectance, we found out the transformation matrix of this system. In the final step, we chose other color patches to verify our system through the spectral reconstruction algorithm.

3. SYSTEM DEVELOPMENT

Figure 2 (a) shows the multispectral imaging platform, which consists of an integrating sphere, spectrally tunable LED-based illuminants, and a multi-channel imaging sensor. Integrating sphere is used to provide a stable and uniform lighting condition. Here we chose LED as our illuminants rather than halogen lamp. Although halogen lamp is able to provide a broadband spectral power distribution (SPD), it requires filters or gratings to achieve orthogonally spectral component. LED-based active illuminant consists of 8 types of LEDs, which are red, dental blue, true green, cyan, amber, warm white, cold white and Near-UV. The spectrally-tunable LED lighting system can help us create arbitrary spectral distribution (SPD) of illuminant. By mixing and tuning the LEDs, our purpose is to estimate the spectral reflectance of an object. RGB-channel CCD accompanying with two light sources will make six channels. We setup color CCD and spectroradiometer, leaning at the angle of $\pm 8^{\circ}$ by the middle line of the integrating sphere. By measuring the spectral reflectance and imaging the training dataset at the same time, we can build the transformation matrix for the system. Figure 2 (b) (c) shows the control program of our LED lighting system. By changing the percentage of each type of LED, different spectrum of illuminants can be produced. The advantage of this lighting system over the traditional method of using filters is that it is a much more direct way. Also we can avoid the mechanical problem such as the misalignment between filters and CCD.

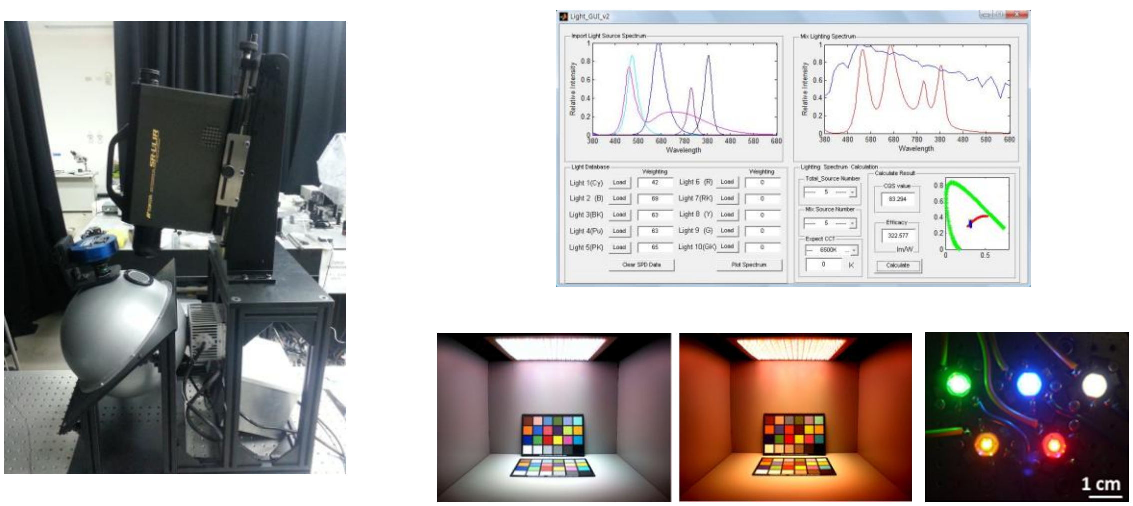

Figure 2: (a) Photograph of the imaging system. The main components includes an integrating sphere, spectro-photometer, multi-channel camera and LED clusters (b) graphical utility interface of spectrally tunable illumination (c) With adequate geometric layout and first-order optical design, we enable a uniform illumination on the color checker.

Figure 3 (a) is the collection of color patches chosen as our training dataset. The number of color patches in our training dataset is near 300. Dual SPDs were used in our study, with cold white (100%) + dental blue (100%) + cyan (100%) and warm white (100%) + red (100%). The two light sources were chosen because they almost cover the whole spectral range of visible light with likely complementary to each other, as shown in Figure 3 (b). In case of moderate color systems based on Munsell's catalog, only six eigenvectors were needed when applying PCA. In our experiments, several combinations of light source have been tested. However, so far we discovered that monochrome light (using single LED) is unlikely to reconstruct spectral reflectance with certain level of accuracy. The reason is sharp-distributed SPDs might have a tight margin in sample spectral distribution. With proper arrangement of broadband illuminant pairs, spectral reflectance can be reconstructed by means of transformation matrix. We measured the color patches from the Munsell training database first. These targets were distributed in every hue of the color system. Since the Munsell catalog is a standard collection to represent most general colors in nature scenes, Munsell-based dataset was assumed to be an appropriate candidate in development of transformation matrix.

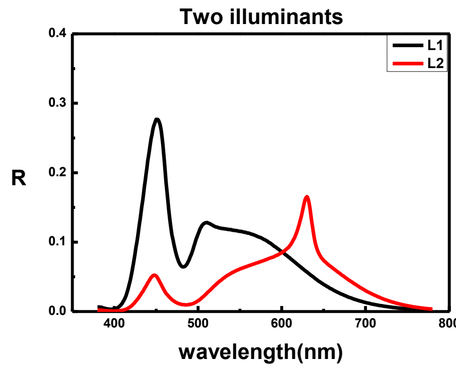

Figure 3 (a) Munsell-based training target (b) SPD of two illuminants. Both SPDs are broadband and complementary to some extent in order to ensure the precision of spectral reconstruction from every hue of the color system.

4. EXPERIMENTAL RESULTS AND DISCUSSIONS

In this paragraph, we will use three other color sample groups to examine the capability of spectral reconstruction of proposed methodology and system. The first group is another four Munsell color patches outside the training database. The second is Macbeth color checkers. The third one is a computer generated print. Three test samples are discrepant in the realm of Munsell-based training database. We will investigate the performance of both spectral reconstruction and the influential factors in accuracy.

Figure 4 is another four Munsell color patches which are not within the realm of our training dataset. Experimental results showed that the reconstructed spectra are in close agreement with those measured by a spectroradiometer. CIEDE2000 and spectral reflectance RMS error were calculated as the quantitative merits. CIEDE2000 accumulates the spectral difference across the entire visible spectrum, thus leads to a reasonable merit for distinguishable judgment for human vision. If CIEDE2000 is smaller than 1, that means the color difference of two patches are unlikely to be distinguished by human vision. Except in case B that the color difference is slightly larger than 1, the reason is due to the hue of that color patch is intermediate : red-yellow. We can see from the reconstruction, in the long wavelength those two lines couldn't fit very well, thus causing slightly larger color difference. However, the overall performance are the best. Since these four patches and our training database are both from Munsell Book of Color. Not only the texture but also the ink are the same.

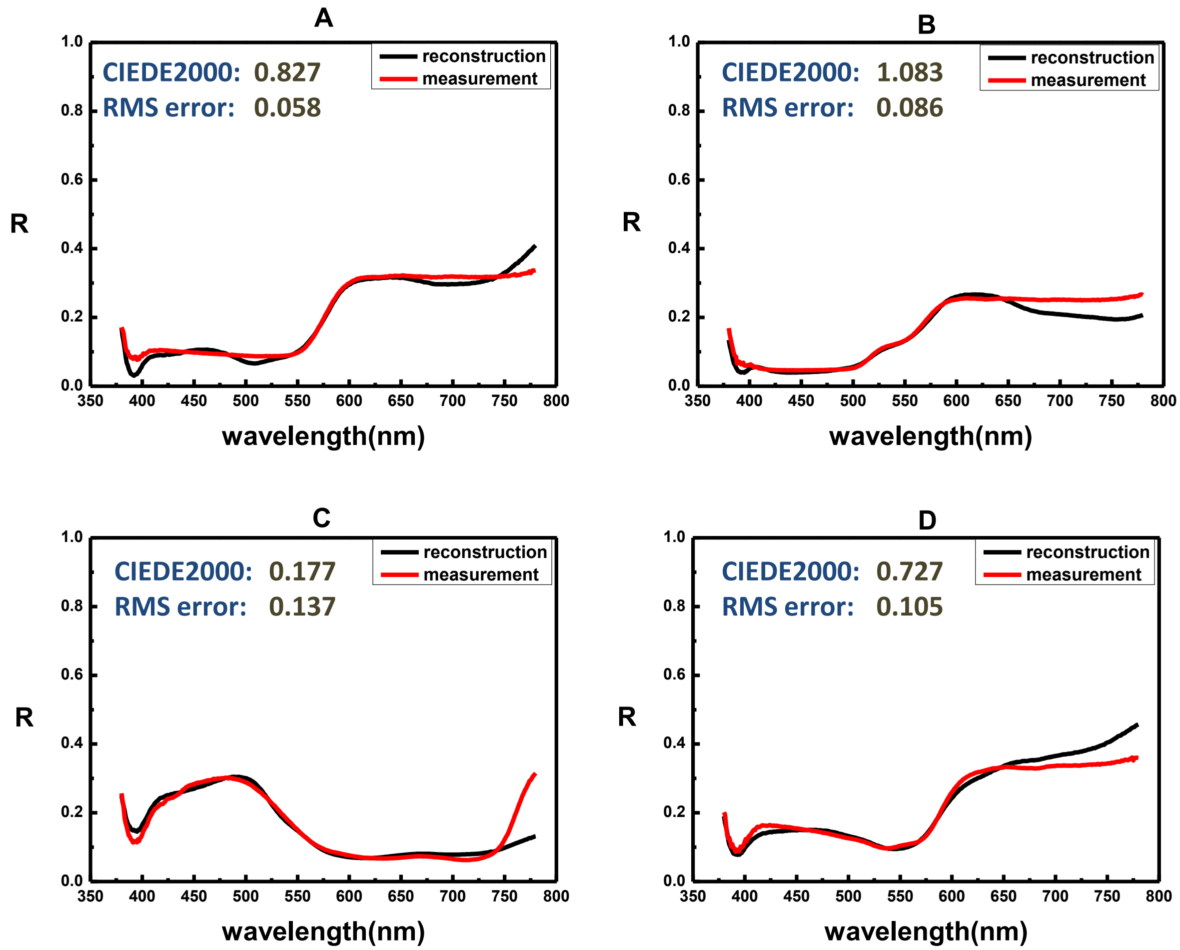

Figure 4: Reconstructed spectral reflectance (black line) and measured spectral reflectance (red line) of four color patches on Munsell Book of Color. Color Difference CIEDE 2000 and spectral reflectance RMS error are calculated. All the four patches have value=6, chroma=8 and with different hue. (A=7.5r, B=7.5yr, C=7b, D=7.5rp)

The second case is the Macbeth color checker, where a standard checkerboard contains the basic colors in most nature scenes. Figure 5 shows five arbitrarily-selected color patches. It's worth noting that #17 (magenta) exhibits a large discrepancy amid the long wavelength region. Color patches of Macbeth have higher color saturation, while our training database mostly belong to moderate colors. The choices of training database can determine the ability of reconstruction, thus influence the color performance of these high-saturated color patches. At last, Figure 6 is a computer generated print. Compared to the former experiment using color checkers, the reconstruction is less accurate, especially in the long wavelength region. The color picture was generated by computer and then printed out by laser printer, since we didn't do the calibration for printer, there might exists color difference in the beginning. In addition, the number of color patches in training database is around 300, there are chances that increasing the color patches number or adding other training samples with different textures and saturations might help to improve the capability of spectral reconstruction for all interested samples.

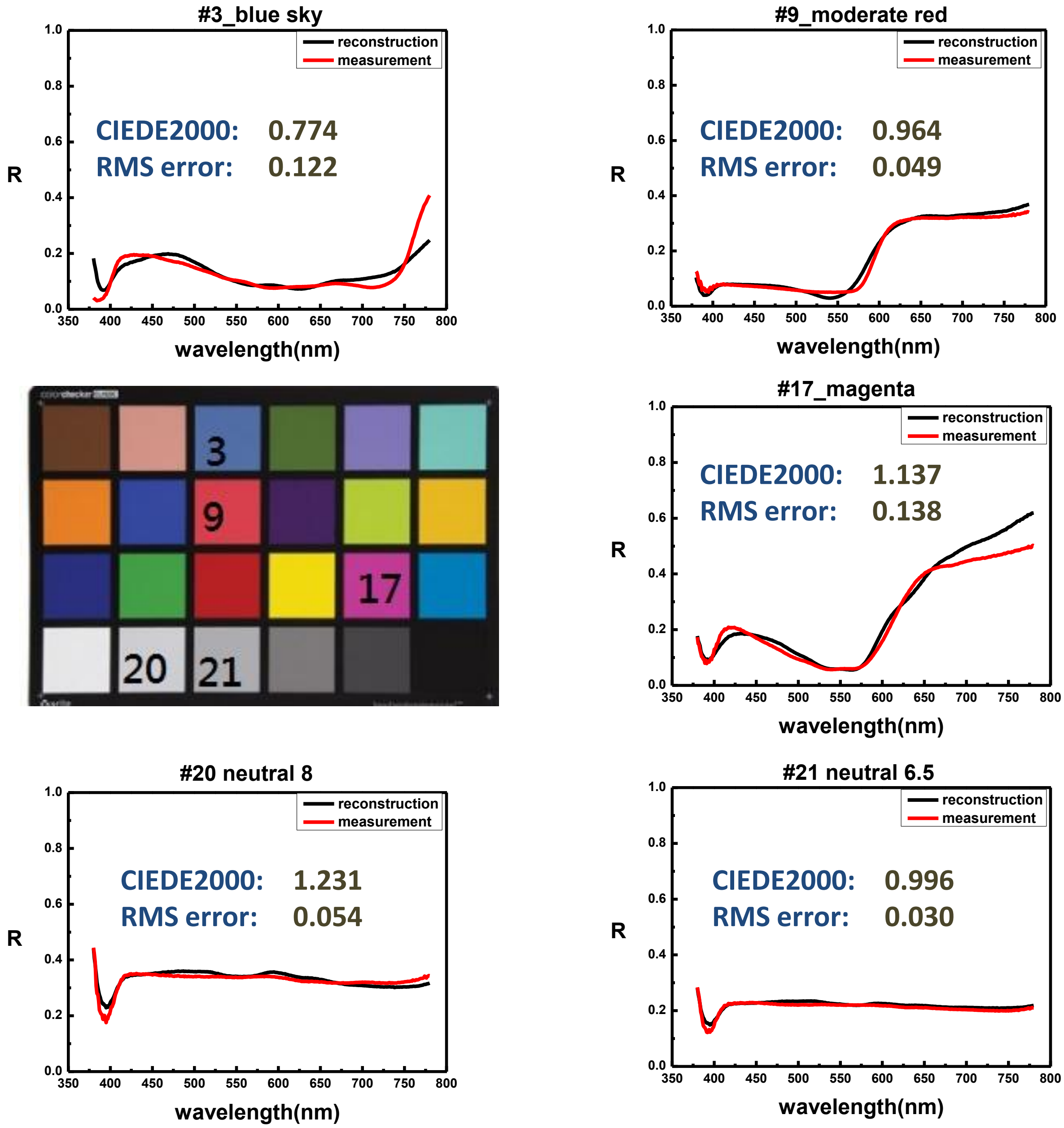

Figure 5: We chose the best five samples over the 24 patches on Macbeth Color Checker that achieve the best reconstruction. Reconstructed spectral reflectance (black line) and measured spectral reflectance (red line). Color Difference CIEDE 2000 and spectral reflectance RMS error are calculated.

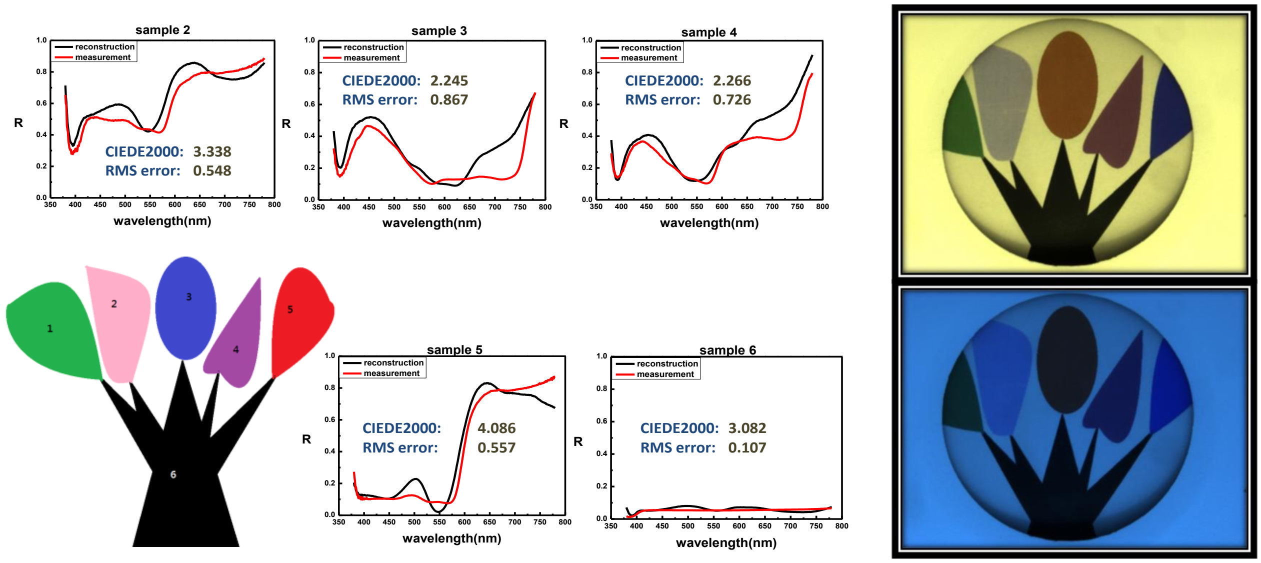

Figure 6: Reconstructed spectral reflectance (black line) and measured spectral reflectance (red line) of computer generate picture. Color Difference CIEDE 2000 and spectral reflectance RMS error are calculated. Right side is the real image retrieved under two illuminants.

5. CONCLUSIONS

In this study, we reconstructed the spectral reflectance of a targeted color patch image by an integrating sphere imaging system and spectrally-tunable LED illumination. Based on the principal component analysis, no additional dispersive elements are required, the reflectance spectra of 34 patches from standard color checker board were estimated with high accuracy (RMS error_ave = 0.234). In order to optimize the estimation transformation matrix for training data, a tunable illumination source such as LED cluster is implemented. Preliminary results validated this full digital restoration process, numerical operation with PCA effectively save the system complicity and computational efficiency without expense of estimation accuracy. Multispectral imaging can provide more color information at each pixel than those with conventional tri-stimulus imaging. As a result, many vision applications stand to benefit. Certainly, there is a huge space yet required for further investigation, such as noise model, statically independence of the spectral target, and stability of LED-based illumination system.

ACKNOWLEDGMENT

This work was finically supported by National Science Council of Taiwan under contract no. NSC 102-2221-E-009 -155 -MY3. Chung-Hao Tien is partially supported by a overseas visiting scholarship from the NSC of Taiwan under contract no 102-2918-I-009-014.

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