High Quality Color Restoration using Spectral Power Distribuion for 3D Textured Model

Akifumi Ikari†(ika@cvl.iis.u-tokyo.ac.jp) Tomohito Masuda†(tom@cvl.iis.u-tokyo.ac.jp)
Tohru Mihashi‡(tohru.mihashi@toppan.co.jp) Kenji Matsudo‡(kenji.matsudo@toppan.co.jp)
Nobuaki Kuchitsu§(kuchitsu@tobunken.go.jp) Katsushi Ikeuchi†(ki@cvl.iis.u-tokyo.ac.jp)

†Institute of Industrial Science, University of Tokyo
4-6-1, Komaba, Meguro-ku, Tokyo 153-8505, Japan

‡Toppan Printing Co.,ltd.
1-3-3, Suido, Bunkyo-ku, Tokyo 112-8531, Japan

§National Research Institute for Cultural Properties,Tokyo
13-43, Ueno Park, Taitoh-ku, Tokyo 110-8713, Japan

Abstract

In connection with efforts to preserve objects of cultural heritage, we are attempting to recreate the real color of a wall painting in the ancient Ozuka tumulus. The difficulties are that there is no sunlight in the tumulus, and we are not allowed to use torchlight because of preservation considerations. So to observe a wall painting under these conditions, we have to observe a computation image. We have found that for high quality color restoration and color preservation, we can use spectral power distribution. We have discovered that a color signal spectral is suitable for color preservation because it has more color data than RGB three-channel data, and it does not depend on a measuring implement. When we use spectral power distribution, we can create images that have more precise colors that those created using RGB data. But the spectral power distribution data that we can acquire has low resolution. So by matching a high-resolution RGB image and a low-resolution spectral power distribution image, we obtain a restored image that has high-resolution and high-quality color.

1 Introduction

Light reflected from an object, usually called a color signal, is the product of two components: illumination spectral power distribution and surface spectral reflectance. Spectral power distribution has not only Red, Green Blue (RGB) data captured by digital camera but also data with greater wavelengths. Spectral power distribution has a great deal of color information that makes possible the analysis of the light source [1, 2, 3, 4], analysis of color and color constancy [5, 6], recognition of an object, componential analysis, creation of a new image when the light source is changed, and so on.

For digital archive or digital preservation of cultural assets, we have measured 3D shapes using a laser range sensor and texture mapping [7, 8] of the data taken by a camera to the 3D data. In some cases, appearance restoration or color restoration is performed by using the 3D data or the picture [9, 10]. Unten et al. [11] recreated color consistent images for texture mapping considering light source condition. But these operations only consider how to map the texture exactly and clearly; they do not consider texture coloring.

In three color channels (RGB), a lot of image processing has been performed, such as color constancy [12, 13], specular removal [14], shadow removal, and so on. In most cases, these processes are successful. But one problem is that the RGB data cannot express the color exactly because RGB data has less information than spectral power distribution data. The relation between RGB data and spectral power distribution data is shown in Section 3. When color restoration or color componential analysis is needed, an RGB image is insufficient. Another problem with using RGB data is that the RGB data value varies depending on the camera. Images of the same object taken by two different cameras will have different RGB values. So for more precise digital preservation or digital restoration of color, we need to preserve the color as spectral power distribution. In this paper, we try to acquire spectral power distribution of wall painting in Ozuka tumulus for digital preservation and restoration.

One problem associated with the use of spectral power distribution, as measured by our system, is that the image restored by this method is a low-resolution image. In this paper, we propose to solve this problem by matching high-resolution RGB data as captured by a digital camera with low-resolution spectral power distribution data, and calculating these RGB data and spectral data.

The rest of the paper is organized as follows. In Section 2, we describe spectral power distribution and introduce a method of acquiring the data of spectral power distribution. In Section 3, we explain the difference between using RGB data and spectral data, the method to change the illumination, and the method of acquiring high-resolution color restoration images under virtual illumination. In Section 4, we show the experimental results of our method. And finally, in Section 5 we conclude our paper.

2 Acquiring Spectral Power Distribution

2.1 Spectral Power Distribution

Spectral power distribution is the data that show the brightness of an object at each wavelength of light. The value of the wavelength most commonly used is the range from 400nm to 700nm, the value that the human eye can respond to. So we can consider that spectral power distribution data has more information than RGB three-channel data. A typical spectral power distribution is shown in Figure 1:Right. Spectral power distribution is the product of illumination spectral power distribution (SPD) and surface spectral reflectance components. Mathematically, it is expressed as:

$$I(\lambda) = E(\lambda)S(\lambda) \tag{1}$$

where $I(\lambda)$ is the color signal at a wavelength λ , $E(\lambda)$ is the illumination spectral power distribution and $S(\lambda)$ ($0 \leqq S(\lambda) \leqq 1$) is the surface spectral reflectance.

When we create an RGB image from spectral power distribution or capture an RGB image by digital camera, the sensor response value ρ_k ($k = red, green, blue$) is expressed as:

$$\rho_k = \int E(\lambda)S(\lambda)R_k(\lambda)d\lambda \tag{2}$$

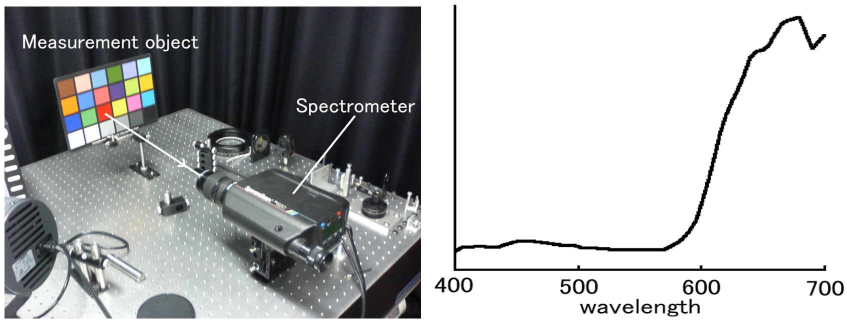

Figure 1: Left: The spectrometer and measurement object. Right: Acquired signal spectral of a red object under sunlight.

Here, $R_k(\lambda)$ is the spectral response curve of the sensors (red,green,blue). The spectral response curve is changed by the kind of camera, human eyes, and so on. When one takes the same object under the same illumination by two cameras, the RGB value is changed because the spectral power distribution is the same but the sensor response is different. So to obtain data that is independent of a measurement instrument, it is best to measure the spectral power distribution $I(\lambda)$.

2.2 Measurement Instrument

There are many ways to acquire spectral power distribution. One of the easiest is to use a spectrometer (Figure 1). By using a spectrometer, we can exactly measure one point's signal spectral. But it is difficult to measure an entire scene's signal spectral. And if one can acquire an entire scene's spectral power distribution by using a mechanical table, many measurement times are needed. So it is not suitable for measuring an entire scene's spectral power distribution.

For measuring an entire scene's spectral, Yoav[15] showed how to use an interference filter. But this requires a mosaicing operation, and it has some parallax problems, so it has low accuracy.

The other way we propose in this paper is to use a line spectroscope (spectral line scanner), as shown in Figure 2:Left. We attach the spectroscope to a monochrome camera, and take an image. Using this equipment, we can take a line signal spectral. The image that the camera, with the spectral line scanner attached, took is shown in Figure 3. By exactly moving this equipment using a control device (rotating, parallel translation, as shown in Figure 2:Right, we can acquire an entire scene's spectral power distribution.

3 High Quality Color Restoration

3.1 Spectral and RGB Illumination change

One of the problems of using RGB data for preservation is that the spectral response curve depends on the kind of camera. If the camera is changed, the value of RGB data is changed, and this is not suitable for preservation.

Another problem is that when we use RGB data taken by a camera, an illumination change operation has errors because RGB data has less information than spectral power distribution.

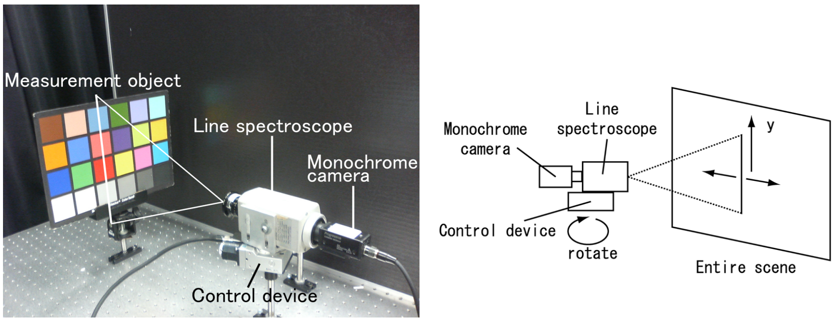

Figure 2: Left: Appearance of measurement of an entire scene's spectral power distribution using line spectroscope. Line spectroscope, monochrome camera, control device and measurement object are shown. Right: An image of the entire scene's spectral scanning.

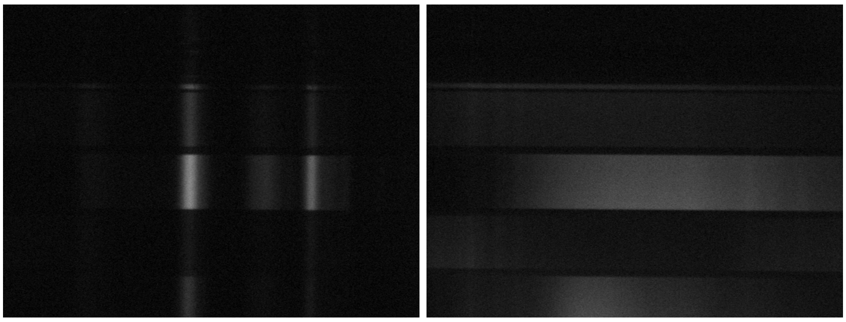

Figure 3: The acquired image using a spectral line scanner. Left: under incandescent light. Right: under sunlight. x-axis shows wavelengths λ from 400nm to 700nm. y-axis is line position y (Figure 2:Right:y). Image intensity expresses the brightness of each wavelength.

We shown it as follows.

When an object ($S(\lambda)$) is captured by a digital camera (the spectral response curve is $R_k(\lambda)$ ($k = red, green, blue$)) under certain illumination ($E_1(\lambda)$), the RGB value ($\rho_{1,k}$) is expressed as follows:

$$\rho_{1,k} = \int E_1(\lambda)S(\lambda)R_k(\lambda)d\lambda, (k = red, green, blue) \tag{3}$$

Then, we take the ambient light's ($E_1(\lambda)$) illumination color using the reference ($S_{ref}(\lambda)$). Often, $S_{ref}(\lambda)$ is independent of λ. It is expressed as follows:

$$Ill_{1,k} = \int E_1(\lambda)S_{ref}(\lambda)R_k(\lambda)d\lambda = \int E_1(\lambda)S_{ref}R_k(\lambda)d\lambda = S_{ref}\int E_1(\lambda)R_k(\lambda)d\lambda \tag{4}$$

Samely, we take an illumination ($E_2(\lambda)$) color that we want to change from the original illumination ($E_1(\lambda)$).

$$Ill_{2,k} = S_{ref}\int E_2(\lambda)R_k(\lambda)d\lambda \tag{5}$$

When an RGB image is used, the following formula is often used.

$$\rho_k = E_k S_k \tag{6}$$

From equation (3) (4) (6), surface reflectance is estimated as follows:

$$S_k = \frac{\rho_{1,k}}{Ill_{1,k}} \tag{7}$$

From (6) (7) estimated RGB value ($\rho^{RGB}_{2,k}$) of the object ($S(\lambda)$) under the illumination ($E_2(\lambda)$) is expressed as follows:

$$\rho^{RGB}_{2,k} = Ill_{2,k} S_k = \frac{Ill_{2,k}}{Ill_{1,k}} \rho_{1,k} \tag{8}$$

The value $\rho^{RGB}_{2,k}$ and real value ($\rho^{real}_{2,k}$: when we take the object $S(\lambda)$ under the illumination $E_2(\lambda)$) is differ. It is expressed as follows:

$$\rho^{RGB}_{2,k} = \frac{\int E_2(\lambda) R_k(\lambda) d\lambda}{\int E_1(\lambda) R_k(\lambda) d\lambda} \int E_1(\lambda) S(\lambda) R_k(\lambda) d\lambda \neq \int E_2(\lambda) S(\lambda) R_k(\lambda) d\lambda = \rho^{real}_{2,k} \tag{9}$$

So for more exact illumination change, it is necessary to use spectral power distribution. But, as mentioned earlier, the problem with using spectral power distribution is the spectral power distribution data is low-resolution data. This is because our scanning device (camera and moving device) has low-resolution and needs greater distance from the object; we need to fix the device and the device size is large, so it is difficult to bring it close. Also, more time is needed in acquisition of an entire scene's spectral power distribution than acquisition of RGB image using a digital camera. It is because when we acquire an entire scene's spectral power distribution, we take thousands of images. But for a digital archive, we need high-resolution data, so we solve the low-resolution problem by using spectral data combined with RGB data.

3.2 Labeling

To achieve a high quality color restored image, we begin with an entire scene's spectral power distribution and RGB data taken by a camera. Then, for data processing, we label the same position between the RGB image and the spectral data. In the case where an object is a plane, it is easily labeled, because by using Affine transformation, we can obtain a same-angle image. In other cases, we use the 3D shape of an object. To measure the 3D shape of an object, we use two types of laser range sensors. One of the sensors is Imager (Z+F), which measures wide data but has low accuracy. Another is VIVID 910 (KonicaMinolta), which has high accuracy measurement but is limited to local area scanning. These multiple measurement data are registered by a fast simultaneous registration method [16], a kind of Iterative Closest Point (ICP) algorithm. From this we obtain one 3D shape, as shown in Figure 4. Then we texture map the RGB image and the spectral power distribution on the 3D data, and we label all instances of the same position between the RGB image and the spectral data.

3.3 High-resolution Illumination Change

To obtain a high-resolution image with changed illumination, we perform the following operation. First, we label between RGB data $I_{1,k}$ and spectral power distribution data $I_1(\lambda)$. Then we measure the illumination spectral power distribution $E_1(\lambda)$ before the illumination change (ambient light when an object is measured) and the illumination spectral power distribution $E_2(\lambda)$ after the illumination change (the illumination that is used to newly light the object).

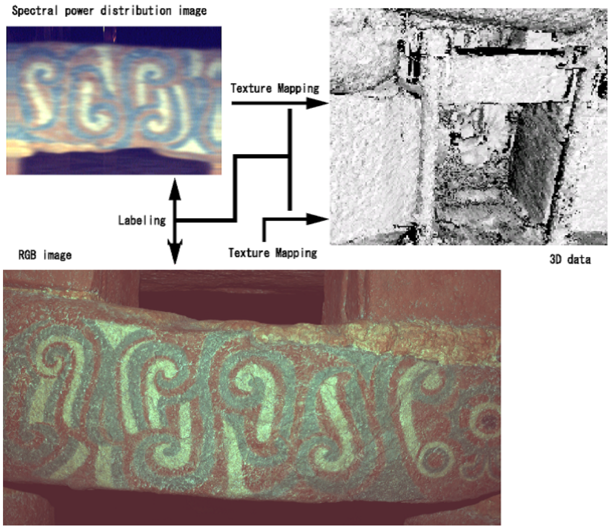

Figure 4: Low-resolution spectral power distribution data is texture mapped on 3D data and high-resolution RGB data. Then the position at which low-resolution spectral data and high-resolution RGB data coincide is labeled.

Then measure spectral power distribution of these illumination ($E_1(\lambda), E_2(\lambda)$) using the spectrometer by measuring white reference: the surface spectral reflectance is independent of wavelength ($S_{ref}(\lambda) = S_{ref}$). From equation (1), when the measured value are I_1^{ref} and I_1^{ref}, these illumination spectral power distribution expressed as follows:

$$E_1(\lambda) = \frac{I_1^{ref}(\lambda)}{S_{ref}(\lambda)} = \frac{1}{S_{ref}} I_1^{ref}(\lambda) \tag{10}$$

$$E_2(\lambda) = \frac{1}{S_{ref}} I_2^{ref}(\lambda) \tag{11}$$

Then, we calculate surface spectral reflectance.

$$S(\lambda) = \frac{I_1(\lambda)}{E_1(\lambda)} \tag{12}$$

From equation (2) (10) (11) (12), we calculate a color signal (RGB) of an object from spectral power distribution. We calculate the case under two states of illumination: the "before" illumination and the "after" illumination.

$$I_{1,k}^{sp} = \int E_1(\lambda)S(\lambda)R_k(\lambda)d\lambda = \int I_1(\lambda)R_k(\lambda)d\lambda, (k = r, g, b) \tag{13}$$

$$I_{2,k}^{sp} = \int E_2(\lambda)S(\lambda)R_k(\lambda)d\lambda = \int \frac{I_2^{ref}(\lambda)}{I_1^{ref}(\lambda)} I_1(\lambda)R_k(\lambda)d\lambda, (l = r, g, b) \tag{14}$$

Where, $R_k(\lambda)$ is a spectral response curve of an camera that take an image. By using equation (13) (14), we propose the following formula to calculate a color signal of an object under new illumination.

$$I_{2,k} = \frac{I_{2,k}^{sp}}{I_{1,k}^{sp}} I_{1,k} \tag{15}$$

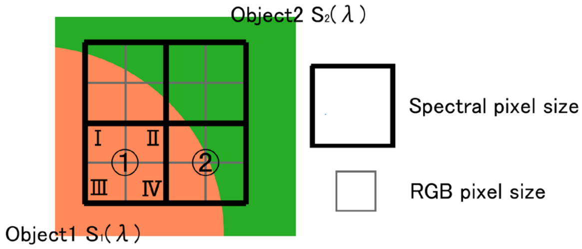

Figure 5: Image of Area that spectral data captured and RGB data captured. Circled 1: Spectral scanner catch only a single object. Circled 2: Catch multi-object.

By this formula, in the case where the spectral power distribution catches the spectral of a single object (Figure 5:circled 1), the changing operation performs perfectly because the case $I^{sp}_{1,k} = I_{1,k}$ is consistent. From equation (9) (15), it expressed as follows:

$$I_{2,k} = I^{sp}_{2,k} = \rho^{real}_{2,k} \tag{16}$$

In the case that catches a multi-object's spectral in one spectral power distribution, the changing operation has errors. Consider the case that the spectral scanner captured spectral of objects (S_1, S_2) (the ratio is $\alpha : 1 - \alpha$ $(0 \leq \alpha \leq 1)$) and a digital camera captured RGB data of these object (the ratio is $\beta : 1 - \beta$ $(0 \leq \beta \leq 1)$). Then, the error's ratio is reduced by nearly $1 - |\alpha - \beta|$. So it becomes more accurate than only using an RGB image.

And more, we consider another method. We consider multi point's RGB data $(I^{p}_{1,k})$ of high-resolution image in same spectral data. Here, p is point's number. And if, in Figure 5:circled 1, it is I to IV. Then, we average it.

$$I^{ave}_{1,k} = \frac{\sum_{p=1}^{n} I^{p}_{1,k}}{p} \tag{17}$$

And then from equation (14) (17), we propose to calculate a color signal of an object under new illumination.

$$I_{2,k} = \frac{I^{sp}_{2,k}}{I^{ave}_{1,k}} I_{1,k} \tag{18}$$

In the case where the spectral power distribution catches the spectral of a single object, the changing operation performs perfectly because the case $I^{ave}_{1,k} = I_{1,k}$ is consistent. In the case that catches a multi-object's spectral in one spectral power distribution, it improve error samely with equation (15). And this method we can change the spectral response curve from our camera's spectral response curve to another simulated spectral response curve. But this operation need more exact labeling.

By these operation, we can acquire an illumination changed image with higher resolution than we could obtain using only spectral power distribution data. We can also acquire a changed image with more precise illumination than we could obtain by using only RGB data. By these operation we can acquire a real image of a wall painting in the Ozuka tumulus despite the lack of sunlight or torchlight.

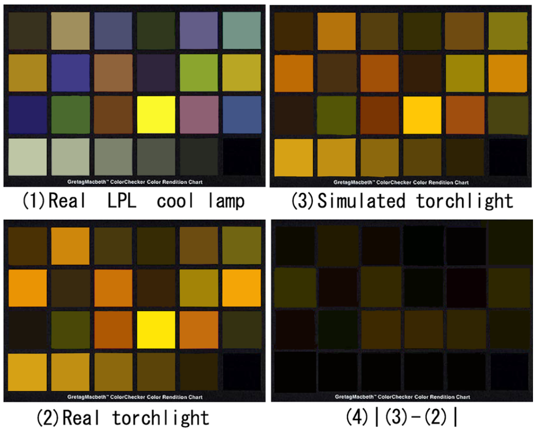

Figure 6: The difference between real RGB data and simulation result using RGB image. (1)Real data under LPL cool light. (2)Real data under Torchlight. (3)Simulation result of the illumination change from LPL cool light to Torchlight only using RGB data. (4)The difference between simulation data and real data.

4 Experimental Results

First, to confirm the difference in illumination changing between a real data and RGB data using the method described in Subsection 3.1, we need to show experimental difference. We took a spectral power distribution and RGB data of Macbeth Color Checker under LPL cool light. As the RGB digital camera, we used Nikon D1x. And as the line spectral scanner we used Specim's Imspector. We used a rotational table (CYUO SEIKI's MM-60θ) as the camera rotational device. We took an RGB image of the Macbeth color checker under LPL cool light. Then we virtually made an RGB image under torchlight using the RGB image, as shown in Figure 6. Finally, we shown the difference in illumination change using only RGB data. Second, we performed an illumination change operation to the Ozuka tumulus data to create a digital archive. We took spectral power distribution of a wall painting of the Ozuka tumulus under LPL cool light. We took an image by digital camera (Nikon D1x) under the same light. And then we labeled points of similarity between these, and changed illumination to sun light and torchlight using equation (15). The operation is shown in Figure 7. And third we perform illumination change using equation (18), it is shown in Figure 8

5 Conclusion

We achieved the digital preservation of an object's color by acquiring spectral power distribution using a spectral line scanner. Using spectral power distribution data, we found that we could preserve an object's color more exactly than by using RGB data. We also found that we could compensate for low-resolution of spectral power distribution data by labeling and combining high-resolution RGB data and low-resolution spectral data. Using calculations to manipulate these data, we achieved high-quality color restoration under changing illumination.

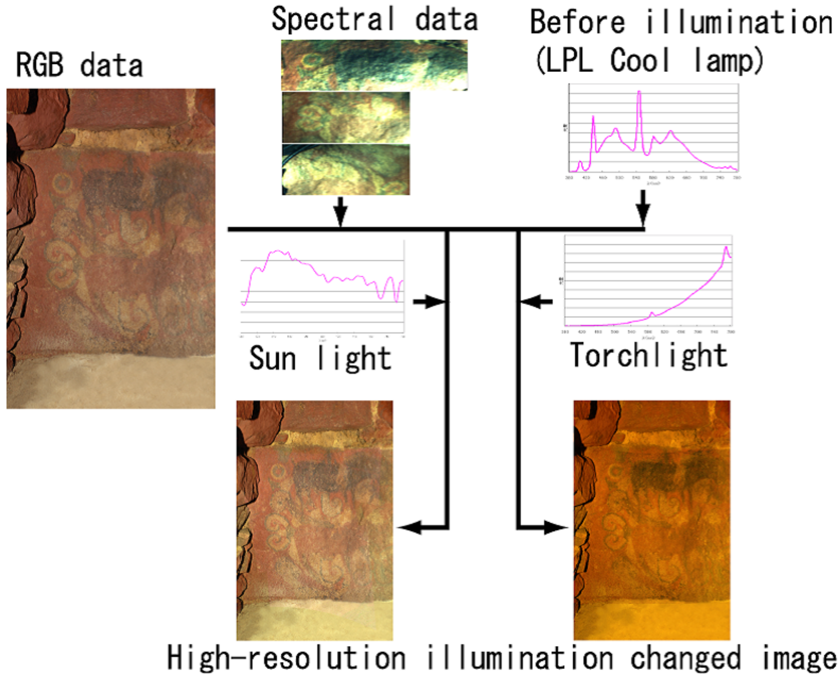

Figure 7: Illumination changing flow of wall paint of Ozuka tumulus. we change illumination from LPL cool light to sun light and torchlight using equation (15).

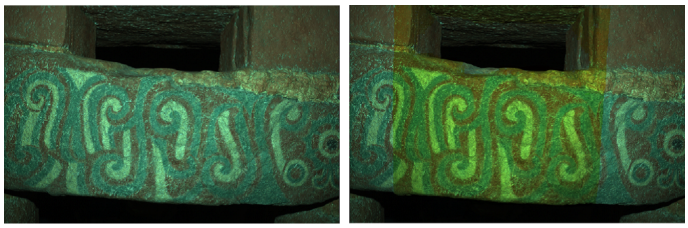

Figure 8: Left: object under LPL cool light. Right: Torchlight data using equation (18).

Acknowledgement

This work was supported in part by the Ministry of Education, Culture, Sports, Science and Technology, under the program "Development of High Fidelity Digitization Software for Large-Scale and Intangible Cultural Assets." We also thank Mr. Kiyoyuki Hasegawa (the Ozuka Painted Tumulus Museum) and the Keisen Town Board of Education for the setup of our measurement, Mr. Isao Ishiyama and Mr. Hiroshi Ishimaru (the Kyushu Historical Museum) for their offering of many pictures of the Ozuka Tumulus, Mr. Kiminori Hasegawa, Mr. Hiroki Unten, Mr. Daisuke Miyazaki, Ms. Rei Kawakami, and Mr. Takushi Shibata (the University of Tokyo).

References

[1] Po-Rong Chang and Tsung-Hsieh Hsieh. Constrained nonlinear optimization approaches to color-signal separation. *IEEE trans. image processing*, Vol. 4, No. 1, pp.

81–93, 1995.

[2] Jian Ho, Brian V. Funt, and Mark S. Drew. Separating a color signal into illumination and surface reflectance components: Theory and applications. *IEEE PAMI*, Vol. 12, No. 10, pp. 966–977, 1990.

[3] Shoji Tominaga and Brian A. Wandell. Standard surface-reflectance model and illuminant estimation. *J. Opt. Soc. Am. A*, Vol. 6, No. 4, pp. 576–584, 1989.

[4] Akifumi Ikari, Robby T. Tan, and Katsushi Ikeuchi. Separating illumination and surface spectral from multiple color signals. *Asian Conference on Compuyrt Vision*, Vol. 1, pp. 264–269, 2004.

[5] John A. Marchant and Christine M. Onyango. Spectral invariance under daylight illumination changes. *J. Opt. Soc. Am. A*, Vol. 19, No. 5, pp. 840–848, 2002.

[6] Th. Gevers, H.M.G.Stockman, and J.van de Weijer. Color constancy from hyper-spectral data. *BMVC*, 2000.

[7] R. Kurazume, M.D. Wheeler, and K. Ikeuchi. Mapping textures on 3d geometric model using reflectance image. In *Data Fusion Workshop in IEEE International Conference on Robotics and Automation*, May 2001.

[8] R. Kurazume, Z. Zhang K. Nishino, and K. Ikeuchi. Simultaneous 2d images and 3d geometric model registration for texture mappint utilizing reflectance attribute. In *Proceedings of Fifth Asian Conference on Computer Vision*, pp. 99–106, January 2002.

[9] T. Masuda, Y. Yamada, N. Kuchitsu, and K. Ikeuchi. Sunlight illumination simulation for archaological investigation - case study of the fugoppe cave -. In *Proceedings of the Tenth International Conference on Virtual Systems and MultiMedia (VSMM 2004)*, pp. 850–859, November 2004.

[10] Interactive Media Lab at Toppan Printing Co.,ltd. VR Theater at Toppan Koishikawa Building. http://www.toppan.co.jp/products+service/vr/intro_e.htm.

[11] Hiroki Unten and Katsushi Ikeuchi. Color alignment in texture mapping of images under point light source and general lighting condition. *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2004.

[12] Graham D. Finlayson and Steven D. Hordley. Color constancy at a pixel. *J. Opt. Soc. Am. A*, Vol. 18, No. 2, pp. 253–264, 2001.

[13] Shoji Tominaga and IEEE Member. Surface identification using the dichromatic reflection model. *PAMI*, 1991.

[14] Robby T. Tan, Ko Nishino, and Katsushi Ikeuchi. Illumination chromaticity estimation using inverse-intensity chromaticity space. *CVPR*, Vol. 1, pp. 673–680, 2003.

[15] Yoav Y. Schechner and Shree K. Nayar. Generalized mosaicing: Wide field of view multispectral imaging. *PAMI*, 2001.

[16] Fast Simultaneous Alignment of Multiple Range Images Using Index Images(in Japanese). Takeshi oishi, atsushi nakazawa, katsushi ikeuchi. In *Meeting on Image Recognition and Understanding 2004*, July 2004.