Multispectral Image Compression for Color Reproduction; Weighted KLT and Adaptive Quantization based on Visual Color Perception

Yuri Murakami[(1)(3)], Hiroyuki Manabe[(2)(3)], Takashi Obi[(2)(3)], Masahiro Yamaguchi[(2)(2)] and Nagaaki Ohayama[(1)(3)]
[(1)] Tokyo Institute of Technology, Frontier Collaborative Research Center,
[(2)] Tokyo Institute of Technology, Imaging Science & Engineering Laboratory Yokohama, Japan
[(3)] TAO of Japan, Akasaka Natural Vision Research Center, Tokyo, Japan

Abstract

An inter-band decorrelation and quantization method of multispectral data are proposed, which are suitable for lossy compression of multispectral images used for high fidelity color reproduction. The proposed inter-band decorrelation method is a modified version of Karhunen-Loeve transform (KLT), called weighted KLT (WKLT), which is designed to minimize the color difference between the color images reconstructed from original and restored multispectral images. For quantization of WKLT coefficients, adaptive quantization (AQ) is introduced in order to equalize the partiality of the perceived error which is caused by the visual nonlinearity between the luminance and the perceived lightness of the color. Through the experiments using 16-band multispectral image of an oil painting, it is confirmed that WKLT followed by AQ reduces the average and the maximum color differences in L*a*b* color space in comparison with the conventional methods composed of KLT and linear quantization.

Introduction

Multispectral imaging becomes an important technology for various color imaging applications that need high fidelity color reproduction; tele-medicine,[1] electronic museum[2] and on-line shopping etc. Using multispectral images and the spectral distribution of illumination light, the spectral reflectances of objects are estimated accurately, so that high fidelity color reproduction is possible under various kinds of viewing illuminations. However, for the efficient transmission, compression technique becomes indispensable.

The compression of multispectral images has been investigated mainly in the filed of remote sensing.[3-5] The compression performance in lossy compression is measured by the difference between the original and the restored multispectral image signal from the compressed bit streams. However, even if the error in the multispectral image signal is small, it cannot be always said that the error in the reconstructed color image from the restored multispectral image is small.

In this paper we propose an inter-band decorrelation method and a quantization method for lossy compression of multispectral images in visual applications, which are designed using the difference between the color images reconstructed from original and restored multispectral images as a degradation measure.

Inter-band decorrelation by WKLT

Weighted KLT

KLT gives the optimum low-dimensional approximation of high-dimensional data through linear transformation and it is often utilized in transform coding. The basis vectors of KLT are chosen to minimize the error

$$\varepsilon_{KLT} = \left\langle \left\| \mathbf{f} - \hat{\mathbf{f}}_M^{KLT} \right\|^2 \right\rangle \tag{1}$$

where <> is an averaging operator, **f** is an original vector and $\hat{\mathbf{f}}_{\mathbf{M}}^{\mathbf{KLT}}$ is *M*-dimensional approximation of **f** expressed by

$$\hat{\mathbf{f}}_M^{KLT} = \sum_{j=1}^{M} \left(\mathbf{u}_j{}^T \mathbf{f} \right) \mathbf{u}_j \,, \tag{2}$$

where superscript *T* denotes the transpose of the vector. Based on KLT algorithm, $\mathbf{u}_j$ are eigen vectors of the correlation matrix of **f** as

$$\left\langle \mathbf{f}\mathbf{f}^T \right\rangle \mathbf{u}_j = \sigma_j \mathbf{u}_j \,, \tag{3}$$

where σ_i is *j*-th eigen value.

In WKLT, we define WKLT approximation error as

$$\varepsilon_{WKLT} = \left\langle \left\| \mathbf{W}\mathbf{f} - \mathbf{W}\hat{\mathbf{f}}_M^{WKLT} \right\|^2 \right\rangle, \tag{4}$$

where **W** is a diagonal matrix and $\hat{\mathbf{f}}_M^{WKLT}$ is the approximation of **f** by WKLT basis functions. If we regard **Wf** as an original vector and $\mathbf{W}\hat{\mathbf{f}}_M^{WKLT}$ as its approximation,

$\hat{\mathbf{f}}_M^{WKLT}$ can be derived in the same way as Eqs. (2) and (3) as follows:

$$\hat{\mathbf{f}}_M^{WKLT} = \mathbf{W}^{-1}\sum_{j=1}^{M}\alpha_j \mathbf{v}_j \, , \tag{5}$$

$$\alpha_j = \mathbf{v}_j^{\,T}\mathbf{W}\mathbf{f} \, , \tag{6}$$

and

$$\left\langle \mathbf{W}\mathbf{f}\mathbf{f}^T\mathbf{W} \right\rangle \mathbf{v}_j = \omega_j \mathbf{v}_j \, . \tag{7}$$

WKLT for Spectral Data

Let us consider the color of the object with the spectral reflectance **f**, denoted by a three dimensional column vector $\mathbf{c}_k$. Since the color depends on the illumination spectrum, k represents the type of the illumination, where the spectral intensity is given by a column vector $\mathbf{e}_k$. Then we have

$$\mathbf{c}_k = \begin{pmatrix} X_k \\ Y_k \\ Z_k \end{pmatrix} = \begin{pmatrix} \mathbf{e}_k^{\,T}\mathbf{T}_X \\ \mathbf{e}_k^{\,T}\mathbf{T}_Y \\ \mathbf{e}_k^{\,T}\mathbf{T}_Z \end{pmatrix} \mathbf{f} \, , \tag{8}$$

where $\mathbf{T}_X$, $\mathbf{T}_Y$ and $\mathbf{T}_Z$ are M-by-M diagonal matrices whose diagonal elements indicate the color matching functions, such as CIE 1931 XYZ color matching functions. We define the measure of the approximation error of $\hat{\mathbf{f}}$ as the norm in CIE 1931 XYZ color space under L kinds of viewing illuminants, denoted by

$$\begin{aligned} \varepsilon &= \sum_{k=1}^{L}\left\langle \left\| \mathbf{c}_k - \hat{\mathbf{c}}_k \right\|^2 \right\rangle \\ &= \sum_{k=1}^{L}\left\langle \left(\mathbf{f}-\hat{\mathbf{f}}\right)^{\mathrm{T}} \left(\mathbf{e}_k\mathbf{T}_X, \mathbf{e}_k\mathbf{T}_Y, \mathbf{e}_k\mathbf{T}_Z\right) \begin{pmatrix} \mathbf{e}_k\mathbf{T}_X \\ \mathbf{e}_k\mathbf{T}_Y \\ \mathbf{e}_k\mathbf{T}_Z \end{pmatrix} \left(\mathbf{f}-\hat{\mathbf{f}}\right) \right\rangle \\ &= \left\langle \left(\mathbf{f}-\hat{\mathbf{f}}\right)^{\mathrm{T}} \left(\mathbf{T}_X\mathbf{R}_e\mathbf{T}_X, \mathbf{T}_Y\mathbf{R}_e\mathbf{T}_Y, \mathbf{T}_Z\mathbf{R}_e\mathbf{T}_Z\right) \left(\mathbf{f}-\hat{\mathbf{f}}\right) \right\rangle . \end{aligned} \tag{9}$$

where $\hat{\mathbf{c}}_k$ is the color vector of $\hat{\mathbf{f}}$ and

$$\mathbf{R}_e = \sum_{i=1}^{L}\mathbf{e}_i\mathbf{e}_i^{\,T} \, . \tag{10}$$

If the number of the illuminants L gets closer to infinite, M-by-M matrix $\mathbf{R}_e$ is thought to be in proportion to the correlation matrix of the illumination spectra. Here, we substitute the correlation matrix of the illumination spectra by a scalar multiple of an identity, which means each spectrum is independent and identically distributed at each wavelength. Though real illumination spectra are usually correlated, this assumption is reasonable because the viewing illuminants have not been decided at all. Then, we have

$$\varepsilon = \left\langle \left(\mathbf{f}-\hat{\mathbf{f}}\right)^{T} \mathbf{T}_{XYZ}^{\;2} \left(\mathbf{f}-\hat{\mathbf{f}}\right) \right\rangle = \left\langle \left\| \mathbf{T}_{XYZ}\left(\mathbf{f}-\hat{\mathbf{f}}\right) \right\|^2 \right\rangle , \tag{11}$$

where

$$\mathbf{T}_{XYZ} = \sqrt{\mathbf{T}_X^{\;2} + \mathbf{T}_Y^{\;2} + \mathbf{T}_Z^{\;2}} \, . \tag{12}$$

As $\mathbf{T}_{XYZ}$ is a diagonal matrix, we can apply WKLT with $\mathbf{W}=\mathbf{T}_{XYZ}$. Then $\hat{\mathbf{f}}_M^{WKLT}$ becomes the approximation of **f** which minimizes the mean square error in XYZ color space.

Inter-Band Decorrelation by WKLT

The process to obtain the WKLT coefficients from multispectral image is described below. First, the spectral reflectance function is estimated from multispectral data through an estimation method such as Wiener estimation. WKLT bases are calculated from estimated spectral reflectance functions of all pixels in the image using the relation of Eq. (7). Next, the spectral reflectance is transformed to the WKLT coefficients through WKLT given by Eq. (6).

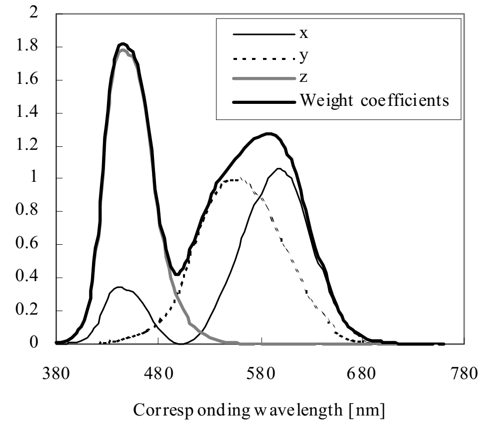

Figure 1. Weight coefficients used in WKLT.

Adaptive Quantization

Error Distribution in Linear Quantization of WKLT Coefficients

Figure 2 shows the error in the uniform color space when WKLT coefficients are linearly quantized, i.e., the color differences vs. the normalized luminance. 16-band multispectral image of an oil painting is transformed by WKLT, and the difference between the colors of the original multispectral image and the color from quantized WKLT coefficients is calculated in CIE L*a*b* uniform color space, E^*_{ab}, under D65 viewing illuminant. Normalized luminance of each pixel, Y/Y_n where Y_n is the luminance of a white object, is divided into 20 levels, then the average error of the corresponding pixels are plotted. This graph shows that the error in the low-luminance colors is extremely large comparing to the high-luminance colors.

The main reason of the error partiality can be thought to be the nonlinearity of visual perception; i.e. the luminance of the light and its perceived lightness are connected with a nonlinear function. One of the models of the relationship is

$$L = Y^{1/3}, \tag{13}$$

where L is a perceived lightness. Based on this characteristic, the method called contrast quantization[7] has been used for monochrome image quantization. In this method, linear quantization is applied after an image signal is transformed to its lightness through the luminance-lightness model function like Eq. (13). Though we cannot show the results of the experiments in which the contrast quantization is directly applied to the WKLT coefficients, because of the restriction on space, it is confirmed that the method cannot improve the performance. The reason can be thought that every WKLT coefficient does not correlate with the luminance of the pixel.

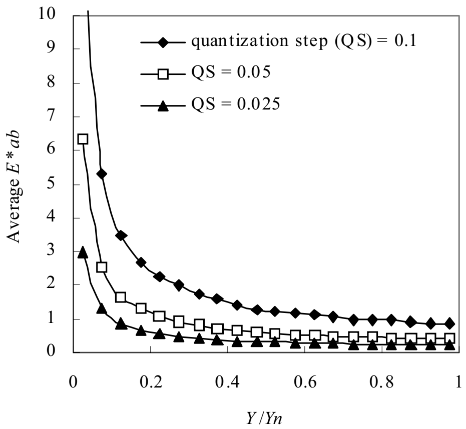

Figure 2. The average E^*_{ab} caused by linear quantization of WKLT coefficients over normalized Y.

Adaptive Quantization

To equalize the error distribution, we propose adaptive quantization (AQ), in which every pixel is classified into several classes depending on its inherent parameter p which is defined to be highly correlated with the average luminance of the reconstructed color pixels under various viewing illuminants. Then, the pixel is quantized at a quantization step decided by the class. As a definition of p, we use

$$p = \sqrt{\sum_{j=1}^{R} \alpha_j^{\,2} \Big/ \sum_{i=1}^{R} \beta_i^{\,2}}\ , \tag{14}$$

where β_i is i-th WKLT coefficients of white object.

Before the explanation of class division, we describe here the model of the error distribution respect with p. If p is defined so that it is highly correlated with the luminance, we can approximate the average perceived lightness $\overline{L}$ of p-value pixels as

$$\overline{L} \cong \gamma p^{1/3}, \tag{15}$$

where γ is a constant. Differentiation of Eq. (15) gives

$$\Delta\overline{L} \cong \frac{1}{3}\gamma p^{-2/3}\Delta p\ . \tag{16}$$

Based on the relationship of Eq. (16), we make the model of the average E^*_{ab} of p-value pixels as

$$\overline{E}^*_{ab}(p,q) \cong \Phi(p,q) = p^{-2/3}q\ , \tag{17}$$

where q is a quantization step and a proportional constant is omitted for simplicity.

While there can be several methods for class division, in this paper, it is carried out using the model of Eq. (17) as follows. Let quantization steps of N classes be $s_1, s_2, \ldots, s_N$, where steps are listed in ascending order. N-1 class divisions d_i's (i=1,…,N-1) are decided as the intersecting points between $\Phi(s_{i+1}, q)$'s and $p=e_{\max}$, where $e_{\max}$ is the parameter to be used for class division. The pixel with p between d_i and d_{i+1} is classified into (i+1)-th class. Figure 3 shows those relationships taking an example for N=4. The error can be restrained under $e_{\max}$ over all range of p.

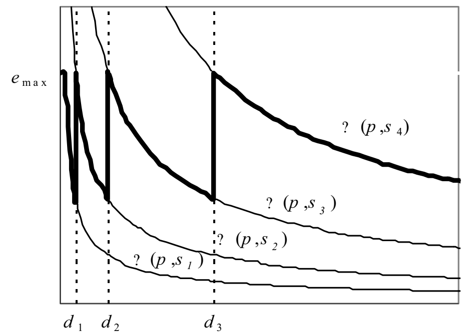

Figure 3. The relationship between e_{max}, $\Phi(p, s_i)$'s and d_i's in case of N=4. Error distribution by AQ is indicated by bold line.

Increasing the number of the classes proceeds with the equalization of the error. However, in AQ, each pixel should has the class information whose number of the kinds is the same as the one of the classes. Therefore, increasing the number of the classes also increases the additional information. Though the investigation on the number of the classes is important issue, this paper shows the results in the case of N=4; the further investigations will be reported in the future publications.

Experimental Results

The multispectral image of an oil painting is captured using multispectral camera (Olympus Opt. Co.,Ltd.) with sixteen narrow band color filters arranged over visible wavelength for the experiments. A band image consists of 640 * 480 pixels having 8 bits gray-level dynamic resolution. The spectral reflectance is obtained by Wiener estimation pixel by pixel using the correlation from 170 spectral reflectances of various natural objects.[8] The KLT and WKLT bases are calculated from the estimated spectral reflectance of all pixels in advance. The estimated spectral reflectances are also used as original to measure the compression error; we call them original spectral reflectances.

Comparison Between KLT and WKLT

To compare the performance of KLT and WKLT, the average and the maximum E^*_{ab} vs. the entropy of the linearly quantized transform coefficients of KLT and WKLT are shown in Fig. 4. In AQ, N=4 and four kinds of quantization steps are s, $2s$, $4s$ and $8s$, where s is the minimum step. The Viewing illuminant is D65. We can see that WKLT improves the compression performance comparing KLT.

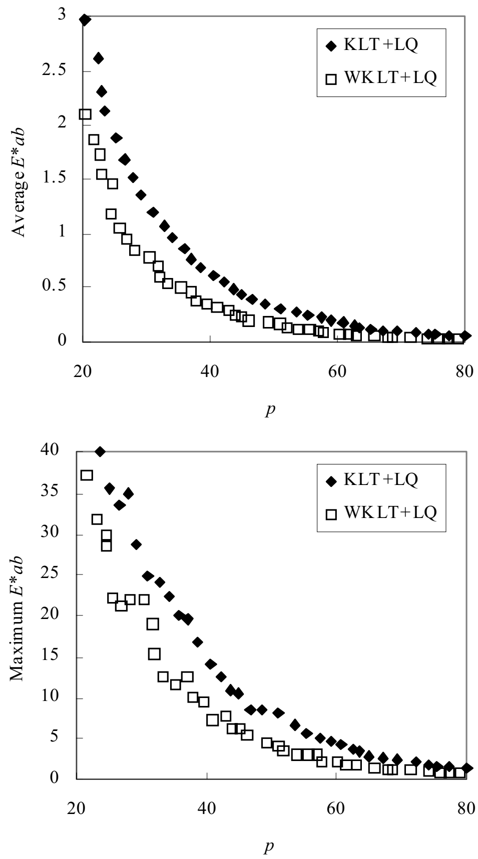

Figure 4. KLT vs. WKLT in compression performance; the upper is average and the lower is maximum.

Comparison Between LQ and AQ

Next, average and maximum E^*_{ab} supposing D65 viewing illuminant caused by linearly and adaptively quantized WKLT coefficients are shown in Fig. 5. The results of LQ of KLT are also plotted. From this result, the maximum error is greatly reduced by introducing the AQ, although there is a little improvement in average error.

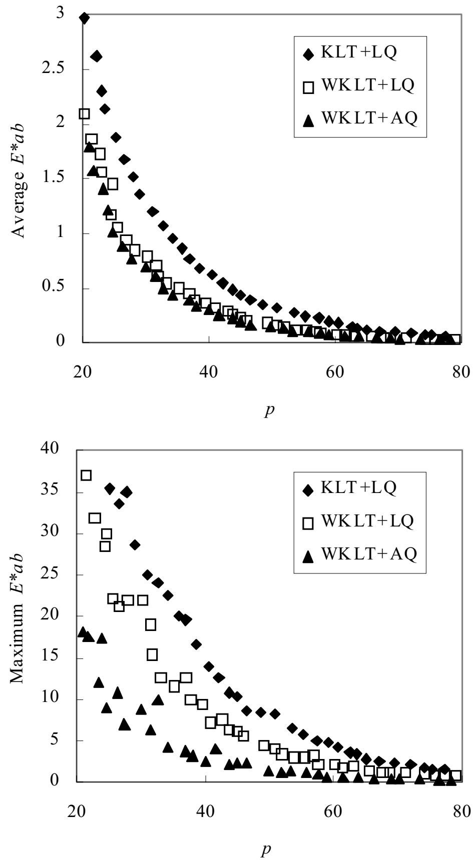

Figure 5. KLT vs. WKLT in compression performance; the upper is average and the lower is maximum.

Table Average and Maximum E^*_{ab} of the compressed multispectral image to about 1/2 and 1/4.

		Average/Maximum E^*_{ab}		
		D65	A	F1
1/2	KLT+LQ (63.41)	0.14/3.47	0.13/2.67	0.16/4.14
	WKLT+LQ (65.66)	0.059/1.40	0.062/1.48	0.059/1.52
	WKLT+AQ (63.70)	0.057/0.61	0.061/0.56	0.056/0.69
1/4	KLT+LQ (31.02)	1.19/24.91	1.10/20.74	1.32/31.11
	WKLT+LQ (31.88)	0.60/15.36	0.58/11.36	0.62/15.41
	WKLT+AQ (31.67)	0.61/6.32	0.62/5.38	0.59/7.75

Average and Maximum E^*_{ab} of the multispectral image compressed to about 1/2 and 1/4 are presented in Table 1; 1/2 corresponds about 64bits/pixel and 1/4 corresponds about 32bits/pixel since original data is 8bits * 16 = 128 bits/pixel. Exact entropy values are presented in parentheses and viewing illuminants are D65, A, F1. From this results, we can see that average error becomes about half by introducing WKLT while the AQ has little effect. In addition, maximum error becomes about half by WKLT and additionally becomes about half by AQ; totally becomes about quarter. This tendency can be seen at every viewing illuminant.

Conclusion

We present WKLT minimizing the mean square XYZ error and AQ which equalizes the E^*_{ab} distribution. As the result of the experiments using 16-band multispectral image of an oil painting, it is confirmed that the proposed method reduces the error in color space in comparison with the conventional method that combines KLT and LQ; average and maximum E^*_{ab} becomes about half and quarter respectively. The combination of the inner-band decorrelation method is being carried out.

References

1. Y. Ohya, T. Obi, M. Yamaguchi, N. Ohyama and Y. Komiya, *Proc. SPIE*, pg. 263-270 (1998).
2. H. Haneishi, T. Hasegawa, A. Hosoi, Y. Yokoyama, N. Tsumura and Y. Miyake, *Applied Optics*, **39**, 35 (2000).
3. T. M. Chen, D. H. Staelin and R. B. Arps, *IEEE Trans. Geosci. Remote Sensing,* GE-25, 4 (1987).
4. S. Gupta and A. Gersho, *IEEE Trans. Geosci. Remote Sensing*, **30**, (1992).
5. J. A. Saghri, A. G. Tescher and J. T. Reagan, Systems & Computers, *Proc. IEEE 27th Asilomar Conf. Signals*, pg. 1342-1346, (1993).
6. F. Kretz, *IEEE Trans. Comm*. COM-23 (1975).
7. A. K. Jain, *Fundamentals of Digital Image Processing*, Prentice-Hall, Inc. Englewood Cliffs, New Jersey, 1986, pg. 120.
8. M. J. Vrhel, R. Gershon and L. S. Iwan, *Color Res. Appl*. **19**, 4-9 (1994).

Biography

Yuri (Ohya) Murakami received her B.S. degree in mathematical and physical science from Japan Women's University at Tokyo, Japan in 1996 and M.Eng. degree information processing from Tokyo Institute of Technology at Yokohama, Japan in 1998. Since 2000 she is a research associate in Frontier Collaborative Research Center of Tokyo Institute of Technology and a fellow researcher of Akasaka Natural Vision Research Center, TAO at Tokyo, Japan. Her work has primarily focused on the color image reproduction using multispectral imaging and multispectral image compression.