Application of PQS for Image Quality Analysis in Visible Spectral Imaging

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Abstract

An image quality investigation in visible spectral imaging was performed. Spectral images were simulated using different number of imaging channels, wavelength steps, and noise levels based on practical spectral imaging systems. A mean opinion score (MOS) was determined from a subjective visual assessment scale experiment for image quality of spectral images rendered to a three-channel display. A set of partial image distortion measures, including color difference for color images, were defined based on classified and quantified actual distortions produced by spectral imaging systems. Principal components analysis was then carried out to quantify the correlation between distortion factors. Finally, a multiple regression analysis (MRA) was carried out between the principal component vectors and the measured MOS values to determine the picture quality scale (PQS). The obtained quality metric, PQS, had high correlation with the subjective measure, MOS. The importance of contribution of the distortion factors in the image quality metric was also evaluated.

Introduction

As the applications of visible spectral imaging become increasingly popular,[1,2] image quality studies in this field have been of greater practical interest.[3,4] However, little has been studied on the evaluation of overall quality of spectral images obtained by digital spectral imaging systems. Typically, when designing a wide-band spectral imaging system, it is important to select a proper and appropriate number of channels to capture the images. During the processing stage, while applying the typical principal components analysis (PCA) method, it is important to select a proper number of basis functions and transform matrix to construct the spectral images. Often, one needs to balance the accuracy of spectral information and noise tolerance of the spectral images. In PCA methods, more channels, or more basis functions used, will give more accuracy of reconstructed spectral information. However, on the other hand, more channels or basis functions used will yield more noise in the reconstructed spectral images.[3] Other issues, like the stability of the transform matrix, the selection of an objective function in imaging system optimization, and different wavelength increments when representing spectra by measurement instruments, will also affect the final spectral images. Image quality studies for spectral imaging, therefore, are worth doing.

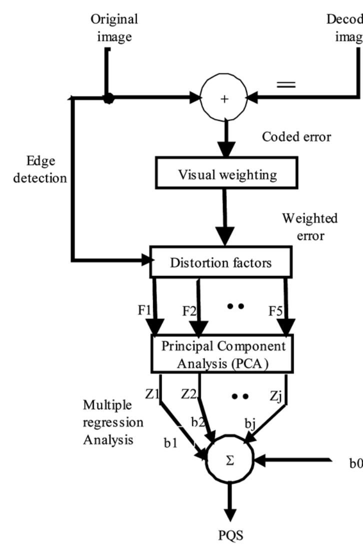

Figure 1. Conventional construction of a PQS system.

This research included visual psychophysical evaluation for spectral images, rendered on an LCD screen. The spectral images were simulated using different noise levels, different basis functions (or channels) and wavelength steps involved in the spectral imaging system designs. To bridge the gap between the physical measures and subjective visual perceptions of the image quality, four image distortion factors were defined and the Picture Quality Scale (PQS) method [5] was employed.

Miyahara's[5] PQS method is widely used for image quality evaluation. As shown in Fig. 1, it was originally proposed for image quality estimation of monochromatic image coding. Based on the perception properties of human vision, a set of partial distortion measures are defined as the function of the error calculated between the original and decoded pictures. The PQS is then calculated from the distortion factors by using principal components analysis and multiple regression analysis (MRA) with the subjective mean opinion score (MOS) obtained experimentally in a quality assessment test. Therefore, the obtained quality metric, PQS, has very good correlation with the subjective measure, MOS. This research only applied the concept of the conventional PQS method to spectral image quality analysis, not the exact step-by-step procedures.

Objective Distortion Factors

Four distortion factors were defined in this research. They were color difference factor for color images, sharpness factor, graininess factor and contrast factor.

Color Difference Factor

When dealing with reproduction of color image color difference equations using S-CIELAB[6] are often selected to evaluate the color accuracy. In this research the detailed procedure proposed by Johnson and Fairchild[7] was followed with a small modification by adding a modulation transfer function (MTF) of the LCD display to the luminance channel.

The spectral images were easily converted into CIE 1931 XYZ images. When displaying on LCD, chromatic adaptation needs to be considered and the LCD device characterization needs to be completed. After these steps, to use the S-CIELAB color difference equation, the first step is to transfer input CIE XYZ tristimulus image, displayed on LCD, into an opponent color space, containing one luminance and two chrominance channels.[6] The opponent color space, AC_1C_2, is a linear transformation from CIE 1931 XYZ. The next step is to perform frequency filtering for each opponent channel in frequency domain. The detail of the frequency filters at this step can be found in reference 7. In this work the only addition is a MTF of the LCD into the luminance channel. The MTF of the LCD was derived based on Barten's[8] method with some practical modification as shown in Fig. 2.

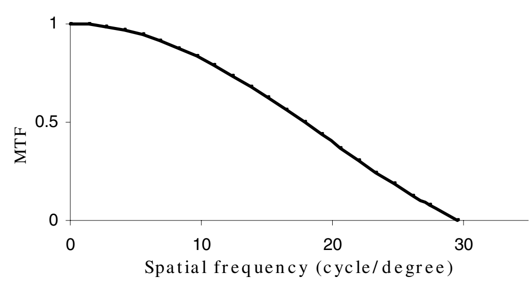

Figure 2. MTF of LCD

The three filters used in this experiment are given in Eqs. 1-3 where csf_{lum}, csf_{rg} and csf_{by} are filters for luminance channel, chrominance red-green channel and chrominance blue-yellow channel respectively and f is spatial frequency in cycles per degree.

$$csf_{lum}(f) = 75 \cdot f^{0.2} e^{-0.8 \cdot f} \tag{1}$$

$$csf_{rg}(f) = a_1 \cdot e^{b_1 \cdot f^{c1}} + a_2 \cdot e^{b_2 \cdot f^{c2}} \tag{2}$$

$$csf_{by}(f) = a_3 \cdot e^{b_3 \cdot f^{c3}} + a_4 \cdot e^{b_4 \cdot f^{c4}} \tag{3}$$

where a_1= 109.1413, b_1= -0.0004, c_1= 3.424, a_2= 93.6, b_2= -0.0037, c_2= 2.168, a_3= 7.033, b_3= 0.000, c_3= 4.258, a_4= 40.691, b_4= -0.104, c_4= 1.649.

Finally, the filtered images were converted back to CIELAB space and the color difference was then calculated pixel by pixel, hence the mean color difference was obtained. In this research, the simple CIE ΔE^*_{ab} color difference equation was used.

Graininess

Often root mean square (RMS) granularity is used as an objective measure in evaluating the graininess of the images.[9] In this experiment, the objective measure of graininess was defined as the RMS error of original and its reproduction images, in the luminance channel of S-CIELAB opponent color space, after filtering as mentioned in previous section.

Sharpness

To evaluate the effect of resolution on perceived image quality, Barten[10,11] proposed the so-called square root integral (SQRI) as shown in Eq. (4).

$$SQRI = \frac{1}{\ln 2} \int_0^{f_{\max}} \sqrt{\frac{M(f)}{Mt(f)}} \frac{df}{f}, \tag{4}$$

where f is the angular spatial frequency at the eye of the observer in cycle/degree (cpd), f_{max} is the maximum angular spatial frequency displayed. *M(f)* is the modulation threshold function (MTF) of the display, and *Mt(f)* is the modulation threshold function of the eye. The inverse of the modulation threshold function of the eye is usually called the contrast sensitivity function (CSF) which is given in Ref. 11. It should be emphasize that SQRI is independent of image content. Researchers[11-13] have indicated that SQRI values were correlated well to the subjective image sharpness for individual images.

Contrast

Calabria and Fairchild[14] proposed an empirical mathematical equation of Single Image Perceived (SIPk) contrast. This equation provides a tool to judge contrast in image without reference to an original image. Though the validity of this equation for other image experiments needs further study, SIPk was selected as the fourth distortion factor in this experiment. SIPk is given in Eq. 5.

$$SIPk = -1.505 + 0.131k_c + 0.151k_l + 666.216k_s, \tag{5}$$

where k_c, k_l, k_s are image chroma standard deviation, lightness standard deviation and the standard deviation of high-frequency lightness image (filtering by Sobel filter) respectively.

Visual Assessment Experiment

Four original spectral images, painting, fruit and two human portraits[2] (one Caucasian one Black) were used as spectral imaging targets in simulation. Two imaging systems were simulated based on two real digital imaging systems. IBM Research PRO\3000 Digital Camera System was applied for spectral imaging of fruit and painting targets and SONY DKC-ST5 Digital Camera was applied for human portraits. The spectral images of fruit and painting targets were simulated using 3-channels, 6-channels and 9-channels wide-band methods by employing 3, 6 and 9 basis functions respectively. The spectral images of the human portrait targets were simulated using 3-channels and 6-channels wide-band by employing 3 and 6 basis functions respectively. The basis functions applied to fruit and painting targets were calculated from Vrhel's[15] data set including 170 natural and man-made object spectra. Basis functions used for human portraits were calculated from our previous spectral imaging experiment.[2]

Five different wavelength increments were used to simulate the spectral imaging capture and reconstruction. They are 2nm, 5nm, 10nm, 15nm and 20nm steps. There are many distinct independent types of noise involved in digital imaging systems. For simplicity and limiting the total number of simulated images for image quality visual assessment experiment, uniformly distributed random noise with three different levels was added into the image capture stage in simulation. They are 0 noise, 1 percent noise and 2 percent noise in terms of the possible dynamic range of the image in each channel. The random noise was channel independent and was created by pseudo-random variable generator using the IDL programming environment.[17] Therefore, including four originals, total of 154 different spectral images were created, 46 for each fruit and painting target, and 31 for each portrait target. These spectral images were then converted into RGB images for LCD to render using chromatic adaptation to the display white point[18] and LCD characterization.

A total of 32 observers, 18 experts and 14 novices, participated in this visual assessment experiment. During the visual experiment two images were rendered on the LCD each time. The observer was asked to assign image quality score for the right side image based on the original image rendered on the left side. The details of the visual experiment are given in the Ref. 16.

Experimental Results

As provided in Eq. (6) the observers were asked to assign an image quality score *A(i,k)* to each image displayed on the right side of the LCD, where *A(i,k)* was the score given by the *ith* observer to image *k*. For each reproduced image, the scores were averaged to obtain the MOS value for a specific image, and n denotes the number of observers.

$$MOS(k) = \frac{1}{n}\sum_{i=1}^{n} A(i,k) \tag{6}$$

The MOS values for four image sets and the relationships between MOS and color difference, graininess, sharpness and contrast factors can be found in the Ref. 16. Generally speaking, they were highly correlated.

Image Quality Metric, PQS

The distortion factors may be correlated since some of the image distortions contributed to several or all factors. The covariance matrix of distortion factors is given at Table 1.

Table 1. Covariance matrix of distortion factors.

	DeltE	Graininess	Sharpness	Contrast
DeltE	1.0000	0.8981	0.1511	0.1586
Graininess	0.8981	1.0000	0.2265	0.0135
Sharpness	0.1511	0.2265	1.0000	0.4777
Contrast	0.1586	0.0135	0.4777	1.0000

The covariance matrix indicates that color difference factor is highly correlated with graininess factor. This is probably due to the fact that the graininess factor was defined as the mean RMS error of original and its reproduction images in the luminance channel which is closely related to the color difference. The correlations are low for the rest of the distortion factors.

The PCA is a good tool to quantify these correlations among distortion factors. By performing the PCA to the four distortion factor data sets, the cumulative contribution percentages of the first one to four principal vectors were obtained and are given in Table 2.

Table 2. Cumulative contribution percentage of principal vectors for distortion actors.

	Number of principal components			
	1	2	3	4
Cumulative percentage	98.90	99.89	100.00	100.00

The results in Table 2 indicate that the first three principal vectors covered 100% of all variance of four distortion factors. The space spanned by the four distortion factors was essentially three-dimensional. This was consistent with the high correlation between color difference and graininess factors. It suggests that three properly defined distortion factors will describe the impairment of images with the same efficiency as using four distortion factors defined in this research. Furthermore, two properly defined distortion factors will be quite safe to describe most of the coverage of four factors used here since the first two principal components covered as high as 99.89% of the variance as shown in Table 2. This provides us some direction for future research.

To investigate the importance of the four distortion factors in describing the image impairment correlation coefficients between the distortion factors and their principal vectors were calculated. The results are given in Table 3. It indicates that the first principal vector mostly reflected the coverage of color difference and graininess factors. Since the first principal vector covered most the variance of the distortion factors, it may suggest that the color difference and graininess factors were the most important factors in this research. The correlation between the first principal vector and the contrast factor was so low that it is safe to say that the contrast factor contributed very small amount of description in most image distortion. The second principal vector still had high correlation with color difference factor. This further proves that the color difference factor was the most important factor in describing the image impairment in this research when using four distortion factors. The second principal vector also correlated with graininess and contrast factors with the correlation coefficients of over 0.65. Loosely speaking, the order of important from high to low for the four distortion factors is, color difference, graininess, sharpness and contrast.

Table 3. Correlations between distortion factors and their principal vectors.

	Principal components		
Factors	1	2	3
DeltE	0.8927	0.8411	0.4927
Graininess	0.8681	0.6856	0.3695
Sharpness	0.1232	0.1387	0.4014
Contrast	0.0146	0.6674	0.6774

To obtain a numerical distortion measure, or an image quality metric PQS, a multiple regression analysis (MRA) between the principal vectors and the MOS values was performed. The first three principal vectors were employed in this task. First, PQS was expressed in terms of the three principal vectors as given in Eq. 7 where the coefficients were determined from MRA by fitting the MOS, Z_1, Z_2 and Z_3 are first three principal vectors respectively.

$$PQS = -3.41 + 78.19 \cdot Z_1 + 13.32 \cdot Z_2 - 6.38 \cdot Z_3 \qquad (7)$$

Next, the basis vectors can be expressed with respect to the distortion factors. This was done by MRA method. Substituting the basis vectors, in terms of distortion factors, into Eq. 7, PQS was finally obtained with respective to distortion factors. The results is given in Eq. 8.

$$PQS = -3.410 - 0.168 \cdot F_E + 0.103 \cdot F_g + 0.062 \cdot F_s + 0.002 \cdot F_c \qquad (8)$$

where F_E, F_g, F_s, and F_c are color difference, graininess, sharpness and contrast factors respectively. The relationship between PQS and MOS is shown in Fig. 3.

The correlation coefficients between PQS and MOS was 0.92. The mean absolute error between MOS and PQS was 0.41. Given that the subjective image quality scores of the test images had at most precision of 0.5, an average absolute error of 0.41 seems adequate.

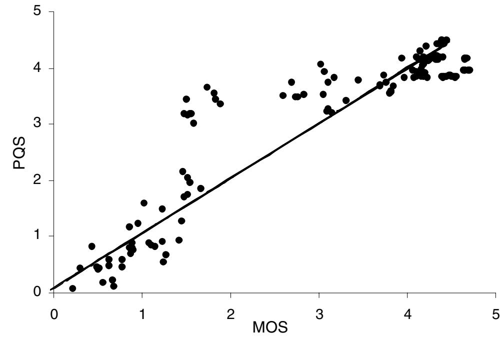

Figure 3. PQS vs. MOS.

Other methods were also tried using direct fit between MOS and distortion factors and the correlation coefficient could be as high as 0.95. Due to the limit of space, the details are not provided here. The importance of contribution of distortion factors in image quality metrics was also investigated. The results indicated that:

1. When using single distortion factor the color difference factor itself was a good image quality metric. PQS repressed by color difference only had as high as 0.953 correlation with MOS.
2. When using two distortion factors in PQS, the combination of color difference and graininess would be the best choice with the correlation coefficient of 0.9211 while the combination of color difference and graininess would be a good candidate. If performing regression directly from the distortion factors, the combination of color difference and contrast factors would provide the best quality prediction with a correlation coefficient of 0.9631.
3. The combination of color difference, graininess and contrast factors would provide the best prediction of image quality when using three distortion factors to represent PQS. The correlation coefficient between PQS and MOS was as high as 0.92. However, when performing regression directly to the distortion factors, combination of color difference, sharpness and contrast factors would provide the best result with the correlation coefficient of 0.9666

It should be noted that the PQS determined by PCA method with MRA tools considered the statistical space distribution of the distortion factors. It did not achieve the highest correlation to MOS by eliminating the impact of some distortion factors, such as the way a simple least square regression directly based on the distortion factors did. Therefore, PQS is more practical flexible and feasible in application than those from simple best fit for specific data, though the latter may have higher correlation to MOS in this experiment.

Limitations of PQS Applications

The distortion factors applied in this research spanned three dimensions. Based on MRA statistical regression techniques, PQS could be reduced to one dimension factor which had a good correlation with image quality MOS. In the statistical regression, the contributions of the distortion factors could be positive or negative. If these contributions were outside the range of which the regression was considered, the results of PQS may be invalid, i.e., situation for extreme low quality range. Thus, a meaningful PQS required meaningful contributions from the distortion factors. As suggested by Miyahara,[5] for the PQS to be meaningful, one requirement is that the weighted contribution of each of the factors as given in Eq. 8 be in the range of one to five. The performance of PQS could be improved by performing piecewise step fit or a further quadratic equation fit of above PQS to get the best final PQS for each range of the image quality.

Conclusions

Spectral images were simulated and a visual image quality experiment was performed. An image quality score MOS (mean opinion score) was obtained. Four distortion factors were defined. Image quality metric, PQS, was estimated and evaluated based on PCA and MRA methods. The high correlation and low mean absolute error between PQS and MOS proved that this approach was successful. Color difference was the most important factor in predicting the color image quality and in itself is a very good image quality metric. The importance of contribution of distortion factors in image quality of spectral imaging systems provided us theoretical guidance in image quality evaluation and further improvement.

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References

1. Di-Yuan Tzeng, Spectral-Based Color Separation Algorithm Development for Multiple-Ink Color Reproduction, Ph.D. thesis, RIT. (1999)
2. Q. Sun and M. D. Fairchild, A New Procedure for Capturing Spectral Images of Human Portraiture, in *9th Congress of the International Colour Association*, SPIE Vol. **4421**, 496-499. (2002)
3. P. D. Burns, Analysis of Image Noise in Multi-Spectral Color Acquisition, Ph.D. Thesis, RIT. (1997)
4. B. Hill, Optimization of Total Multispectral Imaging Systems: Best Spectral Match versus lease Observer Metamerism, in *9th Congress of the International Colour Association*, SPIE Vol. **4421**, 481-486. (2001)
5. M. Miyahara, K. Kotani and V. R. Algazi, Objective Picture Quality Scale (PQS) for Image Coding, *IEEE Transactions on Communications*, **46**, 9, 1215-1226 (1998).
6. X. M. Zhang and B. A. Wandell, A Spatial Extension to CIELAB for Digital Color Image Reproduction, *Soc. for Inf. Disp. Sym. Tech. Digest*, **27**, 731-734. (1996)
7. G. M. Johnson and M. D. Fairchild, A Top Down Description of S-CIELAB and CIEDE2000, *Color Res. Appl.*, in press. (2003)
8. P. G. Barten, Resolution of Liquid-Crystal Display, *SID 91 DIGEST*, 772-775. (1991)
9. J. C. Dainty and R. Shaw, Image Science, Academic Press, INC. New York. (1988)
10. P. J. Barten, The SQRI Method: A New Method for the Evaluation of Visible Resolution on a Display, *Proc. Of the SID*, **28**, 3, 253-261. (1987)
11. P. J. Barten, the Effects of Picture Size and Definition on Perceived Image Quality, *IEEE Tran. On Elec. Dev.*, **36**, 9, 1865-1869. (1989)
12. P. J. Barten, Evaluation of Subject Image Quality with Square-root Integral Method, *J. Opt. Soc. Am. A*, **7**, 10, 2025-2031. (1990)
13. S. Bouzit and L. MacDonald, Colour Difference Metrics and Image Sharpness, *IS&T/SID 8th Color Imaging Conf*, 262-267. (2000)
14. A. J. Calabria and M. D. Fairchild, Compare and Contrast: Perceived Contrast of Color Images, *IS&T/SID 10th Color Imaging Conf*. 17-22. (2001)
15. M. J. Vrhel, R. Gershon and L. S. Iwan, Measurement and Analysis of Object Reflectance Spectra, *Color Res. Appl*. **19**, 4-9. (1994)
16. Q. Sun and M. D. Fairchild, Image Quality for Visible Spectral Imaging, *Proc. PICS*, 210-214. (2003)
17. http://www.rsinc.com/idl/
18. M. D. Fairchild, Revision of CIECAM97s for Practical Application, *Color Res. Appl*. **26**, 418-427. (2001)

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