Image Quality for Visible Spectral Imaging

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Abstract

An image quality investigation into visible spectral imaging was performed. Spectral images were simulated using different number of imaging channels, wavelength steps, and noise levels based on two practical spectral imaging systems. A mean opinion score (MOS) was determined from 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 image quality concerning. The MOS values and distortion measures were highly correlated. The results indicate that the image quality of spectral imaging system is significantly affected by the number of channels used with noise in the image capturing stage. The selection of wavelength steps plays no significant effect on final image quality. The results also showed that the contrast factor plays different effect on image quality for human portraits compared to that on other complex-scene images. An empirical metric was proposed to estimate the image quality. The correlation between this metric and the subjective measure, MOS, is very high with the value of 0.97. Principal components analysis was applied to the distortion factor values. The results indicate that two distortion factor eigenvectors are sufficient to represent four distortion factors used in this experiment. This suggests that further research needs to be performed to find more efficient distortion factors.

Introduction

As the applications of visible spectral imaging become increasingly popular in recent years,[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 visible spectral imaging system, it is important to select proper number of channels to capture the images. During processing stage, while applying principal components analysis (PCA) method, it is important to select proper number of eigenvectors 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. Based on PCA method, more channels or more eigenvectors used will give more accuracy of reconstructed spectral information. However, on the other hand, more channels or more eigenvectors used will yield more noise in the reconstructed spectral images.[4] Other issues, like the stability of transform matrix and the selection of objective function in imaging system optimi-zation, will also affect the final spectral images. Image quality study for spectral imaging, therefore, is worth doing.

This research performed visual psychophysical experimental evaluation for spectral images, displayed on a LCD screen. The spectral images were simulated using different noise levels, different eigenvectors (and channels) and wavelength steps involved in a spectral imaging system. To bridge the gap between the physical measures and subjective visual perceptions of image quality, effort had been made to build the image quality metrics. We applied four image quality metrics in this research. The goal is to find one single metric that is in good correlation to the subjective measure, MOS in this research.

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 the color difference equation using S-CIELAB[5] is often selected to evaluate the image reproduction in color. In this research we followed a procedure proposed by Johnson and Fairchild[6] with a small modification by adding a modulation transfer function (MTF) of the LCD display to the luminance channel. The detail of the frequency filters at this step can be found in Ref. 6. The MTF of the LCD, as shown in Fig. 1, was derived based on Barten's[7] method with some practical modification.

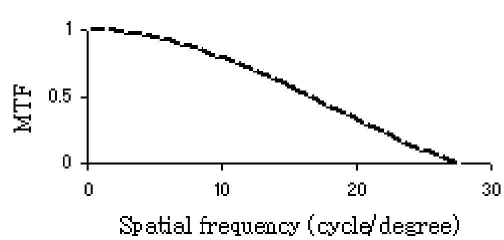

Figure 1. MTF of LCD

Graininess Factor

Typically, root mean square (RMS) granularity is popularly used as an objective measure in evaluating the graininess of the images.[8] 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 Factor

To evaluate the effect of resolution on perceived image quality, Barten[9,10] proposed so-called square root integral (SQRI) as shown in Eq. (1).

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

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 the Ref. 11. It should be emphasize that SQRI is independent of image content. Researchers[11,12] indicated that SQRI values were correlated well to the subjective image sharpness for each individual image.

Contrast Factor

Calabria and Fairchild[13] proposed an empirical mathematical equation of Single Image Perceived (SIPk) contrast. This equation provides us a tool to judge contrast in image without reference to an original image. Though the validity of this equation for other image experiments is questionable and needs further study, SIPk was selected as fourth distortion factor in this experiment. SIPk is given in Eq. 2.

$$SIPk = -1.505 + 0.131k_c + 0.151k_l + 666.216k_s, \qquad (2)$$

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

Spectral Imaging Simulation and Test Images

Four spectral images, fruit, painting and two human portraits[14] (one Caucasian, one Black) were used as original spectral imaging targets in simulation. Two imaging systems were simulated based on two real digital imaging systems. IBM PRO\3000 Digital Camera System was applied for fruit and painting target and SONY DKC-ST5 Digital Camera was applied for human portraiture. The spectral sensitivities of the digital cameras were measured. The spectral images of fruit and painting targets were simulated using 3-channels, 6-channels (by using 202 half C.T. blue filter) and 9-channels (by adding another Kodak Wratten filter #66) wide-band methods. The spectral images of human portraits were simulated using 3-channels and 6-channels wide-band methods (by using 202 blue filter) while the original spectral images were obtained by using 6-channels wide-band method with 2nm step in wavelength. The eigenvectors applied to fruit and painting targets were calculated from Vrhel's[15] data set which including 170 natural and man-mad object spectra. Eigenvectors used for human portraits were calculated from our previous spectral imaging experiment.[16]

Five different wavelength steps were used to simulate the spectral imaging capturing and reconstructing. They are 2nm, 5nm, 10nm, 15nm and 20nm steps. Uniformly distributed random noise with four different levels was also added into imaging capturing stage in simulation. They are zero noise, 1 percent noise, 2 percent noise and 3 percent noise. Therefore, 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 display.

Display Setup

The first step was to characterize the LCD. The accuracy of which in this experiment was 0.14 ΔEab and 0.09 ΔE_{94}. In the next step, spectral images were converted into CIE 1931 XYZ images using illuminant D_{65}. The obtained XYZ images were then converted into XYZ images on LCD using chromatic adaptation.[15] Finally, XYZ images were converted to RGB values for LCD display using the LCD characterization.

The LCD display used in this experiment was a 22'' Apple Cinema Display. The resolution was set to 100 pixels per inch and the brightness was set to peak luminance of 112 cd/m^2. The distance between the observers and the LCD screen was 60cm. Therefore, the visual resolution on the eyes was approximately 41 cycles per degree (cpd). The image sizes displayed on LCD were 550x367 for fruit and painting and 512x640 for human portraits.

Observers

Total of 32 observers, 18 experts and 14 novices, participated in this visual assessment experiment. Each image would be compared to its original and would repeat three times with random order displayed for the observers. The following instruction was provided to the observers:

"This is an image quality visual experiment. We will display two images each time. The image on the left side is the original image, the image on the right side is the reproduction or the original one. Your task is to assign an image quality score to the right side image based on its overall image quality compared to its original on the left side. The quality score definitions are given as the following:

5: Excellent, no distortion is perceptible
4: Good, distortion is perceptible, but not annoying
3: Not good, not bad, slightly annoying
2: Poor, Annoying
1: Very poor, very annoying
0: Bad
You can also assign the score using the step of 0.5.
Thank you for your help and enjoy the experiment."

Experimental Results

MOS Values

As provided in Eq. (3) the observers were asked to assign a score A(i,k) to each image displayed on the right side on the LCD screen, where A(i,k) was the score given by the ith observer to image k. For each reproduced image, the scores were average to obtain the MOS value for a specific image where n donates the number of reproduced images.

$$MOS(k) = \frac{1}{n}\sum_{i=1}^{n} A(i,k) \qquad (3)$$

The MOS values for four image sets are shown in Fig. 2. In Fig. 2, the notation Original represents the original images, 3P3T10nm1N represents the reproduced images using 3 eigenvectors and 3 terms of transform matrix with 10nm step in wavelength and 1 percent noise. The rest of the notations apply the similar definitions. Fig. 2 indicates that image quality, as we expected, does relate to the number of channel used in imaging system when noise is involved. Considering the Fig. 2-a and 2-b, it shows that when using 3 channels, image quality was not significantly affected by the noise involved in capturing stage (within the noise levels used in this experiment). When using 6 and 9 channels, without noise, the image quality does improve a little bit. However, whit noise, the image quality drops significantly; more channels used, more noise effect shown and poor image quality. This is consistent with the theoretical noise analysis results by Burns.[3] For images of human portraits, the quality, shown in Fig. 2-c and 2-d, is in the similar situations as that of 2-a and 2-b. However, portrait images show more sensitivity to noise when using 6 channels compared to using 3 channels. This may be due to the fact that for human portraits, observers were more able to judge the noise appearing on human faces compared to that of more complex scene images in 2-a and 2-b. In all cases, wavelength steps play no significant rule in image quality.

MOS Values versus Color Difference Factor

The relationship between the MOS values and their corresponding mean color differences between the originals images and their reproductions is shown in Fig. 3. The correlations between MOS values and mean color differences were 0.983, 0.986, 0.970 and 0.976 with R^2 values of 0.973, 0.970, 0.941 and 0.952 in linear regression for Figs. 3 (a) to (d) respectively. They correlate very well.

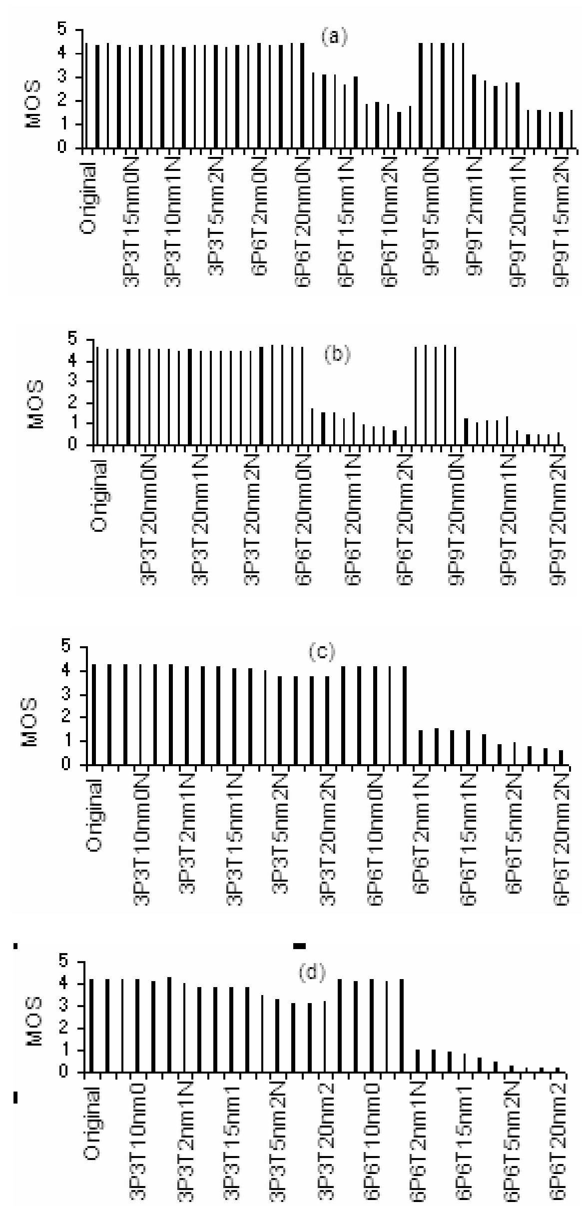

Figure 2. MOS values. MOS for (a) fruit image set; (b) for painting image set; (c) for Caucasian image set; (d)for Black image set.

MOS Values versus Sharpness Factor

The sharpness factors were calculated using Eq. 3. The relationships between MOS values and sharpness factors are shown in Fig. 4. The sharpness factors correlated with MOS values very well with correlations of 0.946, 0.949, 0.850 and 0.952 and R^2 values of 0.908, 0.907, 0722 and 0.907 in linear regression for Fig. 4(a) to (d) respectively.

MOS vs. Graininess Factor

Figure 5 shows the relationship between graininess factor values and MOS values for fruit, painting, Caucasian and Black image sets respectively. The correlations between MOS and graininess values for each image set are

0.95, 0.93, 0.93 and 0.93 with R^2 values of 0.902, 0.856, 0.874, and 0.874 in linear regression respectively. High graininess value is corresponding to low image quality.

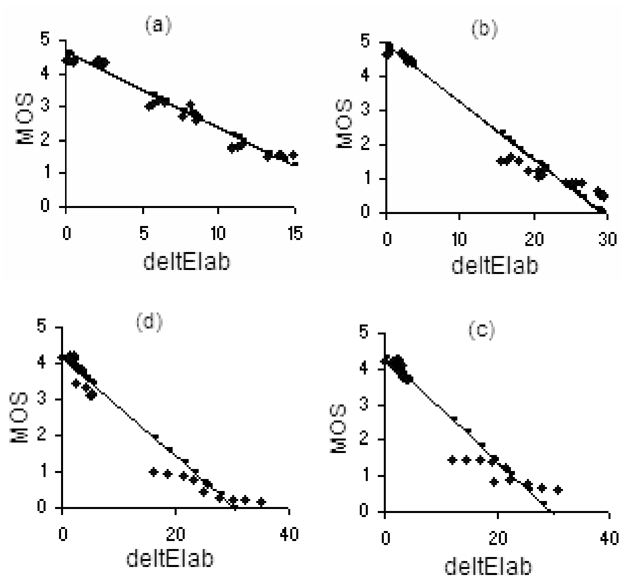

Figure 3. MOS values vs. Mean Color Difference.(a)For fruit images; (b)for painting images; (c) for Caucasian images; (d) for Black images.

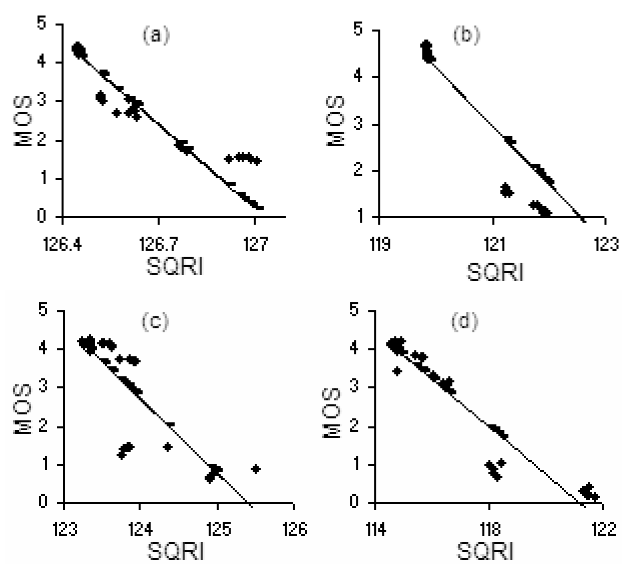

Figure 4. MOS values vs. Sharpness Factors. (a) For fruit images; (b) for painting images; (c) for Caucasian images; (d) for Black images.

MOS vs. Contrast Factor

The relationship between MOS and contrast factor values are shown in Fig. 6 where we divided the SIPk values in Eq. 2 with 10^3. The correlations between MOS values and contrast factor values are 0.988, 0.709, 0.873 and 0.901 with R^2 values of 0.977, 0.503, 0.763 and 0.812 in linear regression for Fig. Fig. 6 (a) and (b) indicate the images with high contrast values display high quality. However, for human portraits, high contrast factor values will display low image quality. The reason is unknown and needs further investigation.

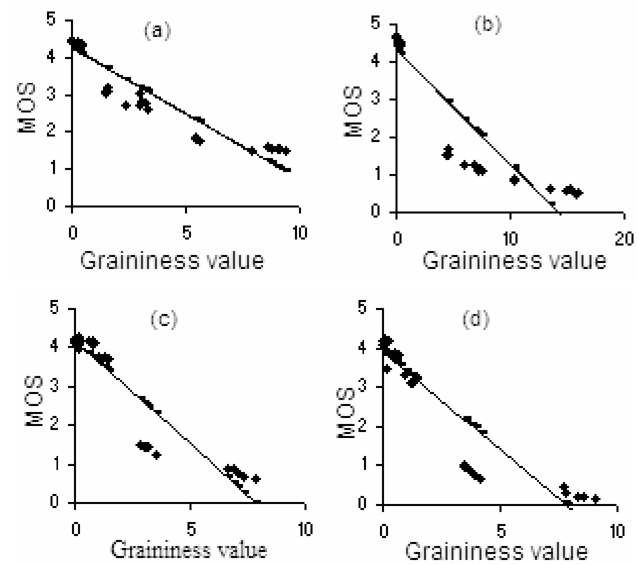

Figure 5. MOS values Graininess Factors. (a) For fruit images; (b) for painting images; (c) for Caucasian images; (d) for Black images.

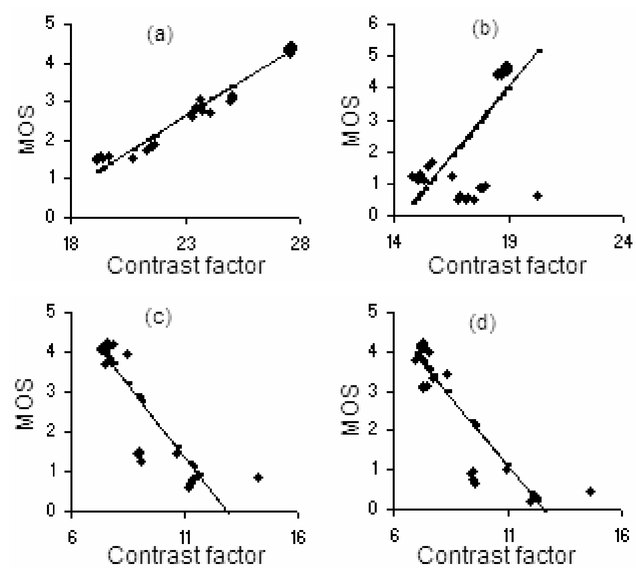

Figure 6. MOS values Contrast Factors. (a) For fruit images; (b) for painting images; (c) for Caucasian images; (d) for Black images.

Empirical Quality Metric

A multiple regression analysis (MRA) was carried out between MOS values and distortion factors to determine one single image quality metric. The result is given in Eq. 4, where E is the color difference factor, G is graininess factor, S is sharpness factor, C is contrast factor and Qm is the quality metric. The correlation between MOS and Qm is 0.97 and with R^2 value of 0.94. Figure 7 shows the relationship between MOS and Qm.

$$Qm = 6.07 - 0.1455E^{0.831} - 0.625G^{0.51} - 0.00387S^{1.305} + 0.254C^{0.351} \quad (4)$$

The distortion factors may be correlated since some of the image distortions contribute to several or all factors. A PCA was performed to quantify the correlation between distortion factors. Results indicate that in this experiment, the first two eigenvectors will cover 99.09% and 99.91% of distortion factor variance respectively. Therefore, two eigenvectors are sufficient enough to represent these four distortion factors.

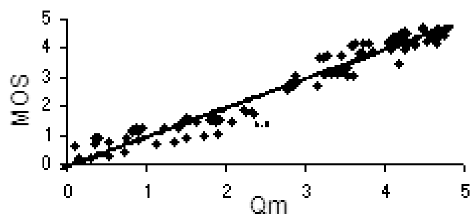

Figure 7. MOS vs. Qm

Conclusions

When noise is involved, to capture and reconstruct spectral images in spectral imaging system, the number of channels or number of eigenvectors selected plays significant effect on final image quality. The wavelength steps do not have much effect on image quality for spectral imaging system. Contrast factor shows opposite image quality effect on human portraits and other complex-scene-images in this experiment. The distortion factors defined in this experiment are highly correlated. Further research needs to be performed to find more efficient distortion factors.

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Biographies

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