マルチ分光における画像圧縮の予備的考察

今井フランシスコ秀樹、 ミッチェル.ロゼン、 ロイ.バーンズ、大田登、松代信人*

ロッチェスター工科大学、＊沖データ

Preliminary study on spectral image compression

*Francisco H. Imai, Mitchell R. Rosen, Roy S. Berns, Noboru Ohta and Nobuhito Matsushiro**

*Rochester Institute of Technology and *Okidata Corporation*

Abstract

Spectral reproduction techniques have many advantages over the traditional methods in terms of robustness to any arbitrary illuminant and observer but they require much more disk space for storage. Few image compression techniques which take advantage the specific nature of spectral images have yet to be explored. Spectral images have higher degrees of redundancy among their multiple channels than do RGB images. It is possible through carefully constructed methods to reduce the redundancy in the spectral and spatial dimensions without considerably affecting the accuracy of the spectral reflectance estimations. Approaches which reduce spatial and spectral sampling rates and precision demands without injuring the reconstruction process are considered. Techniques which include an arithmetic coding step may prove to be promising.

1. Introduction

The inherent metameric aspects of the traditional graphic arts image capture approach of photographing an object and then scanning the photograph has adversely affects the image quality of color reproduction. While it is possible to produce pleasant pictures, large color distortions can result during the image recording and display processes using conventional means. These problems become critical when imaging artwork for archiving and reproduction purposes. It is well known that the only way to assure a color match for all observers and across changes in illumination is to achieve a spectral match. Recent research has investigated this image acquisition paradigm.[1-14] To achieve a spectral match, spectral properties of a scene are modeled, the scene is captured using a multi-channel device and the acquired multi-channel image representation is processed to derive a spectral description of the original scene. Since this involves imaging with more than the traditional three channels, problems arise with respect to processing time and storage. Clearly, some spectral image compression should be considered. Multispectral image compression has been emerging as an important field of study.[15]

Various methods can be exercised to reduce the level of redundancy and noise within and between the spectral channels. This can be performed in a lossless fashion or trade-offs may be made between accuracy and spectral image size. It is possible to classify the redundancy as three types: spatial, spectral and precision dimension redundancies. Images can be compressed in the spectral dimension by reducing the spectral sampling rate. In the precision dimension, it is possible to decrease the number of channels and bit depth used in spectral reconstruction. In this paper, we investigate the influence on colorimetric and spectral accuracy of the number of spectral channels, discussing bit depth and sampling rate. We also discuss some possible ways to perform spatial multi-spectral compression.

2. Spectral and precision dimensions of the spectral imaging acquisition

In multi-spectral acquisition we basically increase the sampling increment above the traditional three channels. The goal is to capture images in an equivalent fashion to using a spectrophotometer at each pixel sampling the visible spectrum at a constant bandpass and wavelength interval. This is in contrast to the traditional three channel approach which is conceptually like sampling each pixel with a densitometer or, at best, a colorimeter. The most straightforward way to capture spectral images is using spectrophotometry. Although spectrophotometer accuracy requirements have not been defined by the Commission Internationale de l'E´clairage (CIE),[16] tristimulus errors are assumed to be negligible using a 5 nm wavelength increment and bandpass. Ideally, one would want to sample every 5 nm with a 5 nm triangular bandpass throughout the visible spectrum. This corresponds to 61 channels. Obviously, it is necessary to reduce the number of channels. One should be able to decrease the sampling increment without a significant loss of spectral information because of the absorption characteristics of both man-made and natural colorants. Spectral analyses of colored stimuli using linear modeling techniques typically result in less than ten eigenvectors.[17-18] For example, we measured the spectral reflectances of the GretagMacbeth Color Checker rendition chart and two set of painted patches. One of the painted patches consisted of 218 patches generated by mixtures of six acrylic paints. The other painted target consisted of oil painting, that we call Ross target (painted by Ross Merrill, a conservator working at the National Gallery of Art, Washington, D.C.). This target was created using 68 pigments representing blues, greens, yellows, reds, earth colors, browns and radiant colors that are among the most frequently used by artists. The measured reflectances were used to perform eigenvector analysis. Table I shows the cumulative contribution rate in function of the number of eigenvectors used in the spectral estimation. Table II shows the dependence of colorimetric and spectral accuracy of the spectral estimation on the number of eigenvectors used in the reconstruction.

Table I. Cumulative contribution of the eigenvectors in reflectance space.

Number of eigenvectors	Cumulative Contribution (%)		
	GretagMacbeth ColorChecker	Painted patches Acrylic	Ross Target
3	98.34	98.50	97.28
6	99.80	99.83	99.61
9	99.97	99.98	99.93
12	100.00	100.00	99.99

Since we used 6 colorants for the acrylic patches it is expected that 6 eigenvectors would be sufficient for the spectral reproduction of these patches. However, this spectral estimation also had a very good accuracy for the Ross target that used 68 different oil paints. From Tables I and II it is possible to conclude that Six basis vectors seem to be sufficient for an accurate spectral reconstruction of artwork.

Thus one should be able to greatly reduce the number of channels from 61. Considerable research has been performed in determining the minimum number of channels needed as well as spectral analysis for optimal filter design,[1,14] and how the multichannel information is used for spectral estimation. Issues include colorimetric accuracy, spectral accuracy, and noise propagation. For example, there is research at the Munsell Color Science Laboratory which has used a typical monochrome digital camera in conjunction with a set of available interference filters.[2] Other projects have worked with a wide-band approach based on trichromatic cameras in conjunction with absorption filters.[5] Both methods are based on *a priori* spectral analysis of samples.

Table II. Influence of the number of eigenvectors in reflectance space used in the spectral reconstruction on the colorimetric and spectral error. ΔE^*_{94} calculated for D50 and the 2° observer.

Number of eigen vectors	GretagMacbeth ColorChecker		Acrylic painted patches		Ross Target	
	Mean ΔE^*_{94}	rms error	Mean ΔE^*_{94}	rms error	Mean ΔE^*_{94}	rms error
3	3.1	0.032	4.1	0.027	3.1	0.042
6	0.3	0.013	0.4	0.009	0.7	0.017
9	0.2	0.007	0.1	0.004	0.2	0.019
12	0.002	0.002	0.01	0.001	0.04	0.012

In terms of equations, a set of spectral reflectances, **r**, is measured and then the corresponding set of eigenvectors, **e**, is calculated by principal component analysis. Then, the set of eigenvalues, α, corresponding to the eigenvectors, **e**, is calculated using the spectral reflectances, **r**. A relationship between eigenvalues and digital counts, **C** obtained using trichromatic camera and absorption filters can be established by the equation

$$\mathbf{A} = \alpha \mathbf{C}^{\mathbf{T}}[\mathbf{C}\mathbf{C}^{\mathbf{T}}]^{-1} \qquad (1)$$

where **T** denotes transpose matrix.

The matrix **A** can be used to calculate the eigenvalues, α, from digital counts to reconstruct the spectral reflectance. This calculated matrix is used for subsequent spectral reconstruction from the camera signals. Therefore, we just need to store the original multi-channel images, the eigenvectors (obtained by *a priori* analysis) and the transformation matrix. If the estimated reflectance has 31 channels and the captured multi-spectral image has 6 channels, the stored image has approximately one fifth of the size of the full spectral image. The sampling rate can also be decreased to generate a spectral image with less channels. However, it is important to notice that decreasing dramatically the sampling rate can compromise the spectral accuracy of the estimated image. Most colors signals are sufficiently bandlimited to allow sampling at 10nm for imaging applications.[19]

The number of available bits also has a large effect on accuracy. Artwork viewers are sensitive to changes in bit-depth for color images[20] and a 10 bit quantization has been found to yield acceptable results.

3. Spatial dimension of the spectral imaging acquisition

In terms of spatial resolution compression, we devised an image fusion method[4,21] shown in Figure 1. This method combines high spatial resolution lightness image L*(x,y) (where x, y are the coordinates of the high spatial resolution image) with low spatial resolution multi-spectral image. From the low spatial resolution channels it is possible to derive a transformation from digital signals to reflectance R'(x',y',λ) (where R' denotes low spatial resolution reflectance and x',y' are the coordinates of the low spatial resolution image, λ is the wavelength). From R'(x',y',λ) it is possible to derive L*a*b* (x', y') that will be combined with lightness image L*(x,y) in order to give the CIELAB values for the high spatial resolution image L*a*b*(x,y,λ). Other researchers also realized the potentialities of this approach.[22]

The estimation of high-resolution spectral reflectance R(x,y,λ) from low-resolution reflectance R(x',y',λ) is based on the Wyszecki hypothesis that any stimulus can be decomposed into a fundamental stimulus (with tristimulus values equal to the stimulus) and a metameric black (with tristimulus values equal to zero) whose mathematical technique, known as Matrix R, was developed by Cohen.[23] The metameric black from R(x',y') will be fused with the fundamental stimulus from L*a*b*(x,y) resulting in a high-resolution spectral image R(x,y,λ), and the same techniques used to combine CIELAB images will be used to merge spectral information. This method can decrease the storage space since the spatial resolution of multi-channel can be decreased and the lightness image will keep the fine details of the image.

4. Spectral Image Compression

The previous sections showed evidences that multi-spectral images have a high degree of redundancy in spatial, spectral and precision dimensions. Figure 2 shows the flowchart of the possible studies involving multi-spectral compression.

We believe that it is possible to devise a multi-spectral image compression method using arithmetic coding as entropic coding as shown in Figure 3.[24-25]

The arithmetic coding allows dynamic reconfigurability and the probability function to be included in the coding. The code is generated from the eigenvector coefficients.

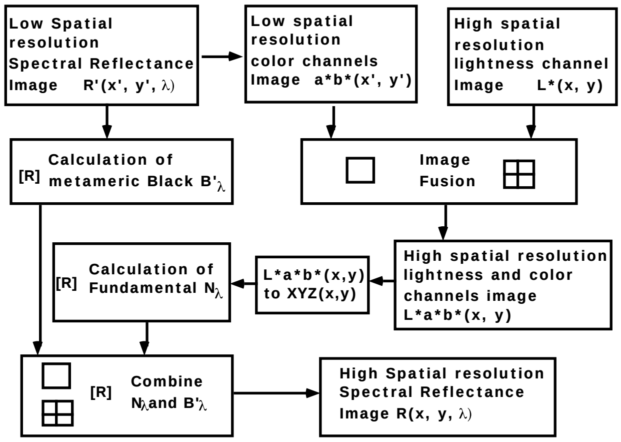

Figure 1. High spatial resolution image reflectance reconstruction using image fusion.

It is important to consider the influence of reducing redundancies in spectral, spatial and precision dimensions on the overall image quality. Therefore, psychophysical experiments should be performed in the future to evaluate the compressed images. At the same time spectral image quality metrics should be derived other than color difference equations and spectral reflectance root mean square error. Hopefully the derived quality metrics will correlate well with the psychophysical experiments.

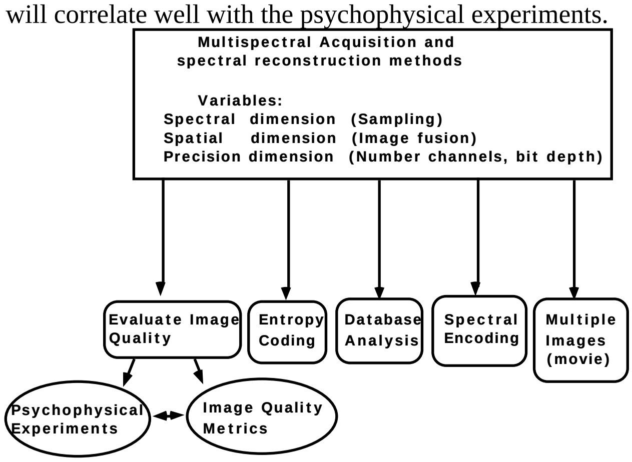

Figure 2. Flowchart of multi-spectral compression research possibilities.

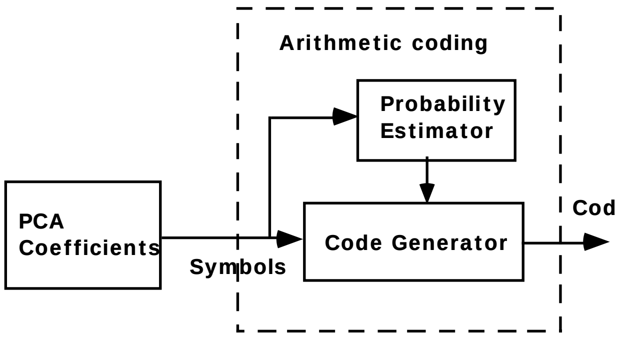

Figure 3. Arithmetic coding for spectral images.

Other fields of study that are closely related to the spectral image compression are the database analysis and spectral encoding. Since spectral images are generated, an efficient way to store, search, process and display should be considered. This also implies that the format of the spectral image (spectral encoding) also needs to be addressed.

5. Conclusion

We have presented many aspects that can contribute to the redundancies of spectral images in the spectral, spatial and precision dimensions. Dynamic range, sampling rate, number of channels used for spectral image estimation and spatial resolution can be used to decrease the size of the images but they also affect the quality of the spectral image. These redundancies can be explored to derive a compression technique for spectral images. A compression method based on arithmetic coding is proposed for spectral images. This method takes in account the entropic information of the eigenvector coefficients to compress spectral images.

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