Multispectral Texture Model for Color and Highlight Reproduction

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Abstract

In this paper, a multispectral texture model for color and highlight reproduction is considered. The model accurately copies the natural image characteristics to synthesize the multispectral images to represent color. This technique based on multispectral image statistics has been used in photorealistic image coloring. Only the spectrum and gray level image are used as initial information in the coloring algorithm. The model feasibility is shown by color reproduction for a synthetic multispectral image with comparison to color reproduction of an original multispectral image. In addition, the on-line image coloring application based on the model is described.

Introduction

In this paper, color and highlight in texture reproduction are considered. This approach can be used in computer graphics and scientific visualization.

The color analysis and reproduction technique is widely used in many applications. To synthesize multispectral texture extensions of the simultaneous autoregressive, Markov and pseudo-Markov random field models were developed, based on the RGB color model.[1] Model parameter estimation was used in a set of natural color samples and the synthetic color images from the estimated parameters were generated. These models are effective at capturing the essential characteristics of natural textures.

Color and highlight analysis used in applications is mainly based on the dichromatic reflection model for inhomogeneous dielectric materials including surface reflection color and body reflection color. An overview of three approaches to highlight analysis and two new techniques for color synthetic and real images is presented.[9] These techniques are efficient for matte image reproduction, robust elimination of highlights. However, the techniques need either cluster analysis or analysis based on several images of the same scene (e.g. ”spectral differencing technique", "local analysis technique") to compute reflection parameters.

There is also highlight and spike analysis for multispectral images. In a dual representation of spectra all spectra are decomposed into a smooth background and a collection of spikes.[10] This model gives realistic image synthesis, especially for rendering light dispersion and diffraction.

A method for estimation of various parameters of a reflection model from a single image taken by a multiband video camera is proposed.[11] Six image components are used and pixels are mapped in a six-dimensional histogram and then reflectance parameters are estimated. Although, the method is six-dimensional it copies a way used for color images and needs previous cluster analysis.

The technique presented in this paper describes images in the spatial and spectral domain and has better descriptive completeness compared with color methods. Also, the method deals with a group of pixels taken from a texture region with similar spectra. Preliminary analysis and modeling show new results on color and highlight reproduction through multispectral representation.[5,4] Three image regions are considered: highlight, light and shade. A highlight reproduction algorithm based on high order statistics is quite formal and can be realized without preceding analysis.[5]

In this study the full multispectral image model is discussed. The model describes images with several dozen components. The highlight and color reproduction factors are presented in the model. The model feasibility is tested in the following way. The given multispectral texture image is reproduced as a color image used for comparative purposes and a gray level image used as initial data. In addition, the mean spectrum computed for the given image is used as initial data. An artificial multispectral image is synthesized from initial data and is then reproduced as a color image. Finally, the color reproduction results and measured statistics for original and synthetic images are compared. In addition, the on-line image coloring application based on the model is described.

Multispectral Image Model

Preliminary study

The presented model copies natural behavior through image statistic simulation and does not contain heuristic solutions. The natural statistical characteristics for texture regions were studied from three datasets.[2,6,7] Results of multispectral statistic analysis were published.[3,5]

The model operates with statistic spectra presented by statistic vectors where each element was measured as a corresponding statistical parameter in a multispectral image component. These four statistic vectors are mean, standard deviation, skewness and kurtosis. Different parts of the model were earlier presented in different publications: the model part based on low order statistics (LOS)[5] and mathematical aspects of the part that belongs to high order statistics (HOS).[4] The complete model is used in this paper to reproduce realistic color and spectra in the synthetic multispectral image.

The algorithm based on the model supports two conditions: general condition and statistical indeterminacy. In the case of the general condition the statistic vectors are known.

The case of statistical indeterminacy is important because all spectral databases contain one spectral characteristic per color. So, the hypothetical texture database to reproduce color images through a set of gray level images and a set of spectra could contain four statistical spectra per gray level image-color pair. In fact, three spectra are needed if the presented model is used, because a skewness vector is derived from a kurtosis vector.

For statistical indeterminacy only the mean spectrum is known, and standard deviation and kurtosis vectors are computed from it. A single component image is also supposed to be given for the model. The image can be a realistic gray level image or a synthetic one. The model simulates a multispectral image for the given image and spectrum. Then, a color image is reproduced from the synthetic multispectral image using a standard technique.

Next, the model for statistical indeterminacy as a more complicated alternative is considered. In the case of the general condition the real-value analogs of the standard deviation and kurtosis vectors are used. The model is oriented to work with multispectral texture; however, the use can cover a separate object (e.g. inhomogeneous dielectric materials).

Model Parameters

The model is intended for multispectral image synthesis of a given gray level image and spectrum. The given spectrum is used as the mean vector. The vectors for standard deviation and kurtosis are derived from the mean vector.

A multispectral image is composed of a set of component images. The image is characterized by a n-dimensional vector random field $\mathbf{v}(\mathbf{x}) = (v_1(\mathbf{x}), v_2(\mathbf{x}), \ldots, v_n(\mathbf{x}))^T$, where the vector $\mathbf{x}=(x_1,x_2)^T$, and x_1,x_2 are the spatial dimensions, $1,2,\ldots,n$ are indices of the spectral dimension, and T denotes the transpose. Hence, the field $\mathbf{v}(\mathbf{x})$ is characterized

$$v(x)=\mu + D_v\eta(x) + D_c\nu_\mu(x) \tag{1}$$

where μ is a mean vector $\mu = (\mu_1,\mu_2,\ldots,\mu_n)^T$, $\eta(\mathbf{x})$ is a vector random field with zero mean and unit standard deviation for each component $\eta(\mathbf{x}) = (\eta_1(\mathbf{x}),\eta_2(\mathbf{x}), \ldots, \eta_n(\mathbf{x}))^T$, and $\eta_i(\mathbf{x})=\eta(\mathbf{x})$ where $\eta(\mathbf{x})$ is a given normalized gray level image, D_v is a diagonal matrix $D_v = \mathrm{diag}(\sigma_{v1},\sigma_{v2},\ldots,\sigma_{vn})$ where σ_{vi} is a standard deviation element (variable component), D_c is a diagonal matrix $D_c = \mathrm{diag}(\sigma_{c1},\sigma_{c2},\ldots,\sigma_{cn})$ where σ_{ci} is a standard deviation element (constant component), $\nu_\mu(\mathbf{x})$ is a vector random field with zero mean and unit standard deviation for each component $\nu_\mu(\mathbf{x})=(\nu_{\mu 1}(\mathbf{x}), \nu_{\mu 2}(\mathbf{x}),\ldots,\nu_{\mu n}(\mathbf{x}))^T$.

The field $\nu_\mu(\mathbf{x})$ is obtained through histogram transform of elements of $\eta(\mathbf{x})$ and a kurtosis vector $\mathbf{k}$ where $\mathbf{k}=(k_1,k_2,\ldots,k_n)^T$. This transform brings to the gamma probability density function. Extensive description of the model can be found in publications.[4,5]

From a statistical viewpoint Equation 1 is a multispectral extension of a regression model. This can also be considered as the multispectral de-texturing procedure when a multispectral texture is represented by an approximation part μ and texture part $\mathbf{D}_v\eta(\mathbf{x})+\mathbf{D}_c\nu_\mu(\mathbf{x})$.

The following relationships are established for σ as follows[3]

$$\sigma \propto \mu \tag{2}$$

where $\sigma=\sigma_c+\sigma_v$, and for $\mathbf{k}$ as follows[3]

$$k \propto \mu^{-1} \tag{3}$$

Equation 3 means that the elements of a vector $\mathbf{k}$ are approximately inversely proportional to the elements of a vector μ.

Thus, the vector μ approximates the model vectors σ and $\mathbf{k}$. The vector σ (relationship between its component σ_c and σ_v) affects chromaticity or color saturation in light. The vector $\mathbf{k}$ defines highlight effect in texture. Equation 3 gives only one of two additional components that affect highlight. The second component is a forced kurtosis peak component. The forced kurtosis peak usually precedes a mean peak (peak in μ) that takes place in the long wavelength subrange. In this study, only Equation 3 is used for highlight reproduction.

Color Reproduction

The model feasibility is tested as follows: the given multispectral texture image is reproduced as a color image used for comparative purposes and a gray level image used as initial data. In addition, the mean spectrum computed in the given image is used as initial data. An artificial multispectral image is synthesized from initial data and is then reproduced as a color image. Finally, the color reproduction results and measured statistics of original and synthetic images are compared.

An experiment on gray level image coloring was conducted. Several multispectral images were used.[6] The results of the image *horshe5* (corals) and *park4* (forest) coloring are shown in Figure 1 and Figure 2, respectively.

These image regions have a size 40 x 40 x 40. The last dimension is the number of spectral components. The following images for *horshe5* and *park4* are shown in Figure 1 and Figure 2: color reproduction from the original multispectral image (upper left), gray level image reproduction (upper right), color reproduction from the synthetic multispectral image (lower left) (the LOS model presented by Equation 1 where $\nu_\mu(\mathbf{x})=\eta(\mathbf{x})$) and color reproduction from the synthetic multispectral image (lower right) (the HOS model presented by Equation 1).

One can see the contrast improvement, highlight effect and correct shade reproduction for HOS model images in comparison with the LOS model images.

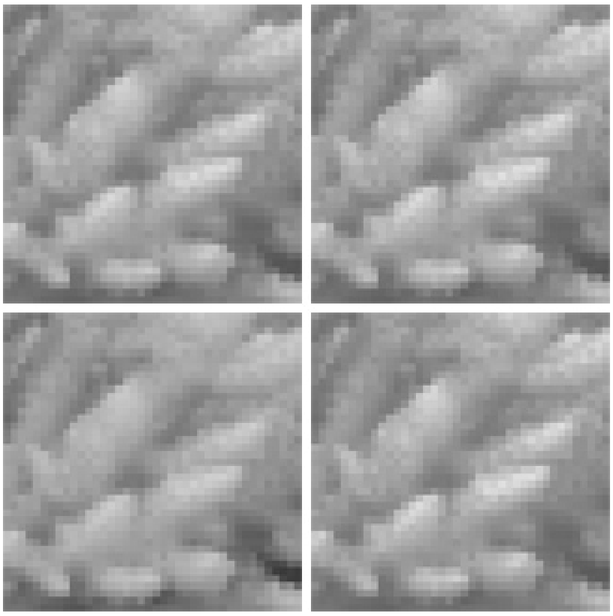

Figure 1. horshe[5]. A color image (upper left) and a gray level image (upper right), a colored image without highlight (lower left) and a colored image with highlight (lower right).

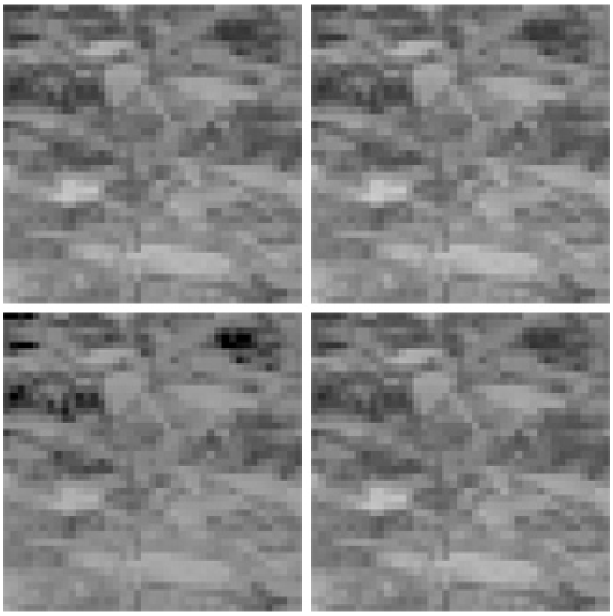

Figure 2. park[4]. A color image (upper left) and a gray level image (upper right), a colored image without highlight (lower left) and a colored image with highlight (lower right)

The statistic measurement results showed also good correspondence between mean, standard deviation, skewness, and kurtosis vectors in natural multispectral images and synthesized multipsectral images.

To estimate the quality of synthesized images, the image criterion ΔE was used. Zhang and Wandell proposed the ΔE measure computed in the S-CIELAB color system which is a spatial extension of the CIELAB system.[12] Average ΔE_{avg} and median ΔE_{med} errors are shown in Table 1.

Table 1. ΔE errors in the S-CIELAB color system.

Image	Model	ΔE_{avg}	ΔE_{med}
horshe5	LOS	4.01	3.46
	HOS	3.35	3.06
park4	LOS	3.37	2.88
	HOS	2.89	2.54

On-Line Application

An on-line image coloring application based on the model is presented on the Web page *http://cs.joensuu.fi/ ~matlab/ gc/gcicframe.html*. Netscape 6 with Java 2 is needed to display the graphical user interface panel.

In an application, a natural gray level image is converted into a synthesized multispectral image by using a real spectrum and a multispectral image statistic simulation. Then, the multispectral image is converted into a color image in the standard way. The synthesized multispectral image consists of 61 components in the range 400 x 700nm taken at 5nm.

Two gray level images used in the application are taken after the conversion of multispectral images into gray level images. The images are *horshe*[29] and *park2*.[6]

12 spectra are taken from database *http://www.it.lut.fi/research/color/database/database.htm*.

Colors corresponding to the spectra are presented in Munsell notation[8]: 10PV5C10, 7.5BV6C10, 10BGV7C8, 10GYV7C10, 2.5YV8C12, 7.5RV5C12, 10PV4C10, 7.5BV5C10, 10BGV6C8, 10GYV6C10, 2.5YV7C12 and 7.5RV4C12.

Graphical user interface includes controls to select an image-color pair. The other controls are highlight, saturation and contrast sliders. The highlight control sets a maximum of $\mathbf{k}$ k_{max} in the range of 3-50. The saturation control sets values in the range of 0-10 at step 1. These values are scaled values in the range of 0-1.0 at step 0.1 and define the weight factor for σ_c and σ_v. The contrast control sets a maximum of $\boldsymbol{\sigma}$ σ_{max} in the range of 0-80.

The highlight control is shown in Figure 3 and the saturation control is shown in Figure 4. Highlight control is used sparingly with a minimal change in light and shade.

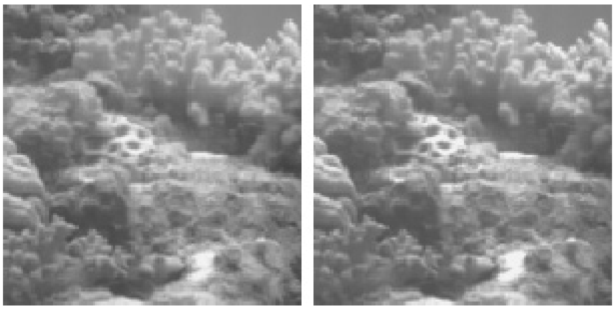

Figure 3. Highlight control: low level (left) and high level (right).

The saturation control is used to set saturation in the light image part. One can see complimentary color in shade against color in light for the right image in Figure 4.

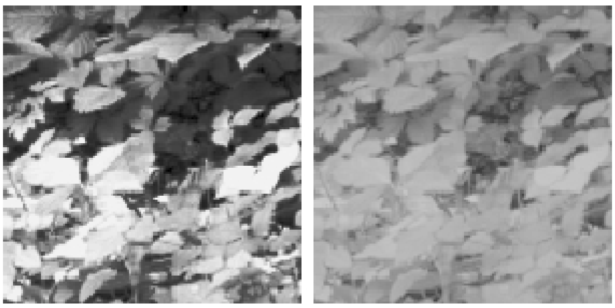

Figure 4. Saturation control in light: low level (left) and high level (right).

Discussion

In this paper, color and highlight in texture reproduction are considered. Only the spectrum and gray level image were used as initial information in the coloring algorithm.

Low and high order statistics were used together to get the colored image reproduced through a synthetic multispectral image. One can see highlight effects and, also, total image contrast improvement. In addition, this technique accommodates correct color reproduction for the light texture part and shade. Measured statistics show the models capability to reproduce images with statistical parameters corresponding to real image statistics.

Thus, the highlight mechanism produces highlight, keeps saturated color in the light and makes a shade not dark. Color in the shade has trend to be complimentary color against color in light at the high level of saturation in light.

The models can be used as a local de-texturing procedure for a composed image. In this case, the statistical vectors $\boldsymbol{\mu}$, $\boldsymbol{\sigma}$ and $\mathbf{k}$ are replaced by corresponding three-dimensional matrices that determine spatial and spectral domain. Since, these statistical matrices are multispectral image approximation wavelets and PCA can efficiently be used for their representation. This method can be used in multispectral image compression technique.

References

1. J. Bennett and A. Khotanzad, Multispectral Random Field Models for Synthesis and Analysis of Color Images, IEEE Trans. Pattern Anal. Machine Intell., 20, pg. 327-332. (1998).
2. V. Botchko, J. Auvinen, O. Makinen, J. Parkkinen and H. Kalviainen, Parametric Multispectral Texture Modeling, Proc. of the 11th Scandinavian Conf. on Image Analysis, Kangerlussuaq, Greenland, pg. 763-769. (1999).
3. V. Botchko, S. El-Gindy, J. Parkkinen and H. Kalviainen, Statistical, Principal and Independent Component Analysis in Multispectral Texture Study, Proc. of the First International Conf. on Color in Graphics and Image Processing, Saint-Etienne, France, pg. 210-213. (2000).
4. V. Botchko, H. Kalviainen, J. Parkkinen, Highlight Reproduction Using Multispectral Texture Statistics, Proc. of the Third International Conference on Multispectral Color Science MCS'01, Joensuu, Finland, pg. 61-64. (2001).
5. V. Botchko, S. Nakauchi, J. Parkkinen and H. Kalviainen, Multispectral Texture Derivation in Virtual Coloring, in Texture Analysis in Machine Vision, ed. M. K. Pietikainen, World Scientific, Series in Machine Perception and Artificial Intelligence, Singapore New Jersey London Hong Kong, pg. 113-126. (2000).
6. C.-C. Chiao, T. W. Cronin, and D. Osorio, Color Signals in Natural Scenes: Characteristics of Reflectance Spectra and Effects of Natural Illuminants, J. Opt. Soc. Am. A, 17, pg. 218-224. (2000).
7. C. A. Parraga, G. Brelstaff, T. Troscianko, I. R. Moorehead, Color and Luminance Information in Natural Scenes, J. Opt. Soc. Am. A, 15, pg. 563-569. (1998).
8. K. Schluns and A. Koschan, Global and Local Highlight Analysis in Color Images, Proc. of the First International

Conf. on Color in Graphics and Image Processing, Saint-Etienne, France, pg. 300-304. (2000).
9. Munsell Book of Color. Matte Finish Collection, Munsell Color, Baltimor. (1976).
10. Y. Sun, F. D. Fracchia and M. S. Drew, Physically Based Dual Representation of Spectral Functions, Optical Engineering, 39, pg. 2931-2942. (2000).
11. S. Tominaga, E. Takahashi, and N. Tanaka, Parameter Estimation of Reflection Model from a Multiband Image, Proc. of the IEEE Workshop on Photometric Modeling for Computer Vision and Graphics, IEEE Computer Society Press, Los Alamitos, Calif., pg. 56-63. (1999).
12. X. Zhang and Wandell B. A., A Spatial Extension of CIELAB for Digital Color Image Reproduction, Proc., Society for Information Display Symposium Technical Digest, 27, pg. 731-734. (1996).

Biography

Vladimir Botchko received his M.Sc. degree in telecommunication from the St. Petersburg State University of Telecommunication at St. Petersburg, Russia in 1973 and a Ph.D. in technical science from the St. Petersburg State Electrotechnical University at St. Petersburg, Russia in 1987. Since 1997 he has worked in the Lappeenranta University of Technology, Finland. His research interests are in the field of multispectral and color image analysis. He is a member of the Finnish Pattern Recognition Society.

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