Nonlinear Enhancement of Extremely High Contrast Images for Visibility Improvement

K. Vijayan Asari, Ender Oguslu, and Saibabu Arigela

Computational Intelligence and Machine Vision Laboratory
Department of Electrical and Computer Engineering
Old Dominion University, Norfolk, Virginia, USA

Abstract. This paper presents a novel image enhancement algorithm using a multilevel windowed inverse sigmoid (MWIS) function for rendering images captured under extremely non uniform lighting conditions. MWIS based image enhancement is a combination of three processes viz. adaptive intensity enhancement, contrast enhancement and color restoration. Adaptive intensity enhancement uses the non linear transfer function to pull up the intensity of underexposed pixels and to pull down the intensity of overexposed pixels of the input image. Contrast enhancement tunes the intensity of each pixel's magnitude with respect to its surrounding pixels. A color restoration process based on relationship between spectral bands and the luminance of the original image is applied to convert the enhanced intensity image back to a color image.

1 Introduction

A human observer can clearly see individual objects both in the sunlight and shadowed areas, since the eye locally adapts while scanning different regions of the scene. The size of pupil is variable to accommodate different levels of radiance from different regions in a scene, while the camera aperture is fixed when capturing the scene. Current imaging and display devices such as CRT monitors (100:1) and printers are limited dynamic range devices. The best photographic prints can provide contrasts up to 10^3:1. But the real world scenes can reach a dynamic range of six orders of magnitude (10^6:1). When attempting to display high dynamic range images into low dynamic range devices, either the low intensity areas, which are underexposed, or the high intensity areas, which are overexposed, cannot be seen. To handle this problem, various image processing techniques such as histogram equalization, gamma correction, logarithmic compression and levels/curves method were developed. They are usually based on global processing, so they have some limitations such as loosing some features during processing, and not enhancing some features. More advanced image enhancement techniques have been developed to obtain better performance. These techniques are able to compress the dynamic range while maintaining or improving local contrast to achieve high visual quality.

Various techniques were developed to deal with images captured in non uniform lighting conditions. Retinex based algorithms developed from E.Land's theory [1] are effective techniques dealing with dynamic range compression and color constancy.

P. Kalra and S. Peleg (Eds.): ICVGIP 2006, LNCS 4338, pp. 240 – 251, 2006.

Rahman *et al*. [2-4] modified the Retinex theory with another center/surround method (Multi Scale Retinex with Color Restoration - MSRCR) which computes the new pixel by a ratio of the treated pixel to the weighted average of the surrounding pixels. The drawback of MSRCR is that the color restoration function changes image chromatics in an unpredictable fashion. To treat this problem dynamic range and color constancy are computed independently. The MSR is only applied to the luminance channel to preserve the chromatics of the original image. Luma dependent nonlinear enhancement (LDNE) [5] processes only the luminance information of the color images instead of all three spectral bands to reduce the processing time. Color noise in shadow/dark areas are suppressed by adding the convolution results instead of multiplying them. In MSRCR and LDNE, dynamic range compression and contrast enhancement are implemented jointly but AINDANE (Adaptive Integrated Neighborhood Dependent Approach for Nonlinear Enhancement) [6] and IRME (Illuminance-Reflectance Model for Nonlinear Enhancement) [7] use separate processes for dynamic range compression and contrast enhancement.

In computer graphics, the tone mapping solves the problem of reproducing the HDR images on LDR devices [8-9]. Larson *et al*. [10] developed a tone-mapping operator based on iterative histogram adjustment and spatial filtering process. The aim of this operator is to produce images that preserve visibility in high dynamic range scenes. Chiu *et al*. [11] considered that tone mapping should be neighborhood dependent. Schlik [12] developed the Chiu's algorithm by using a first-degree rational polynomial function to map high-contrast scene luminance to display system values. This function is not adaptive enough for contrast enhancement for all images. Pattanaik et al. [13] presented a tone-mapping algorithm that represents the pattern, luminance and color processing in the Human Visual System. This algorithm allows not only chromatic adaptation, but also luminance adaptation. However, as other local processing algorithms, it is sensitive to strong halo effects. To eliminate the halo effects, Tumblin and Turk [14] developed a Low Curvature Image Simplifier (LCIS) method. This method can accept inputs from real world image maps and produces necessary output for any device. LCIS separates the input scene into large features and fine details, compressing the former and preserving the latter. This method drastically reduces the dynamic range, but tends to overemphasize fine details. Raanan Fattal [15] used the gradient field of the luminance image for HDR compression by attenuating the magnitudes of large gradients.

A new image enhancement technique named MWISE (Multilevel Windowed Inverse Sigmoid for Enhancement) is proposed in this paper for enhancing the images captured in extremely non-uniform lighting conditions. MWISE is capable of compressing bright regions and at the same time enhancing the dark regions by preserving the main structure of the illuminance - reflectance modality.

2 The MWISE Algorithm

The MWISE algorithm for the enhancement of color images consists of three major constituents, namely adaptive intensity enhancement, contrast enhancement and color restoration. The structure of MWISE is shown in Fig.1.

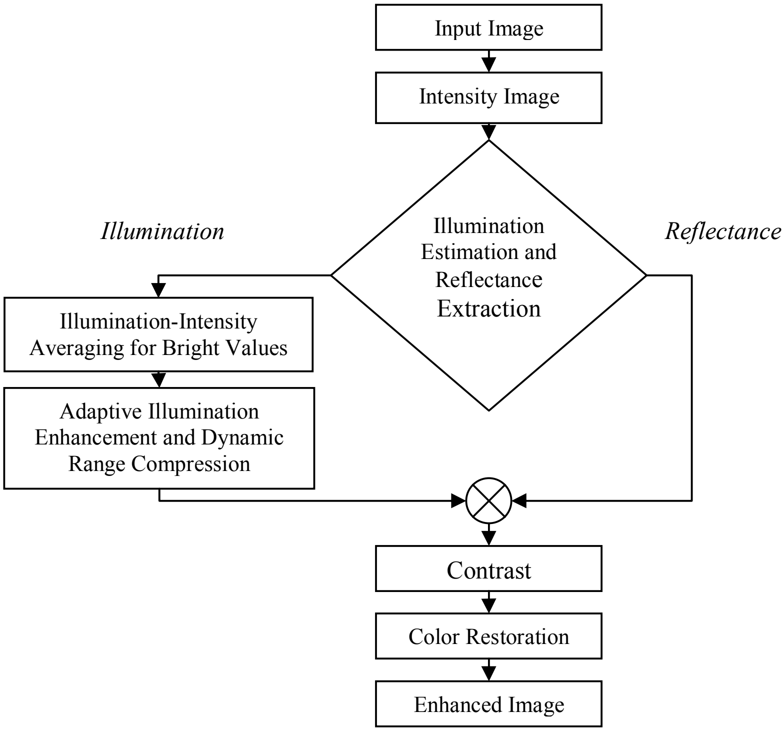


Fig. 1. Structure of the MWISE algorithm for color image enhancement

2.1 Adaptive Intensity Enhancement

First, Color images in RGB color space are converted to intensity (grayscale) images using NTSC standard method defined as

$$I(x, y) = 0.2989 \times R + 0.587 \times G + 0.114 \times B \tag{1}$$

where R, G, B are the red, green and blue components of a color image.

Illumination Estimation. Illumination in an image is characterized by two components: illumination $L(x, y)$ and reflectance $R(x, y)$, and is defined as:

$$I(x, y) = R(x, y).L(x, y) \tag{2}$$

Illumination represents the low frequency components of the image and reflectance represents the high frequency components. Hence a Gaussian low-pass filtered result of the intensity image is considered as illumination, which is obtained as:

$$L(x, y) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} I(m,n)F(m+x, n+y) \tag{3}$$

where F is the 2D Gaussian function with size M×N and can be defined as:

$$F(x,y) = K\exp\left(-\frac{(x+y)^2}{c^2}\right) \tag{4}$$

where $K = \sum_x \sum_y F(x,y) = 1$ and c is the size of the neighborhood.

Averaging Illumination and Intensity for Bright Pixels. The estimated illumination is smooth in the parts of the image illuminated from the same luminous source, but however, it can also present abrupt variation when the scene is illuminated by different light sources in the case of background lights. So, the illumination estimation: for less than 80% of the highest gray scale value (i.e. 255 for 8-bit image) is the illumination which is obtained in (3) and for the other gray scale values, a weighted averaging of illumination and intensity values are given by:

$$L'(x,y) = \frac{I(x,y)-204}{51} I(x,y) + \left(1 - \frac{I(x,y)-204}{51}\right) L(x,y) \tag{5}$$

This averaging produces minimum halo effect in bright regions by reducing the influence of dark neighboring pixels. After obtaining new illumination estimation, the reflectance estimation can be obtained by (2).

Enhancing Dark Illumination and Compressing Bright Illumination. The new illumination value $L'(x,y)$ is normalized to the range [0 10] using (6) and then treated by an enhancement and compression process to increase the illumination values of low-illumination (dark) pixels, and to reduce the illumination values of high-illumination (bright) pixels using the MWIS transfer function.

$$L''(x,y) = \frac{L'(x,y)}{25.5} \quad \text{for 8-bit depth images} \tag{6}$$

Then normalized illumination values are treated by this process also normalizes the illumination values to the range [0 1]. This transfer function can be defined as

$$L''_{enh} = \frac{1}{1+e^{(-\alpha \times L'')}} + \frac{1}{1+e^{(-\beta \times (L''-10))}} - 0.5 \tag{7}$$

where α is a parameter to adjust the curve for dark pixels and β is a parameter to adjust the curve for bright pixels. For adaptive-ness of MWIS transfer function, intensity image is divided into sub images of sizes based on the image enhancement experiments and can be expressed as:

$$m = 0.0625 \times M \qquad n = 0.0625 \times N \tag{8}$$

where m and n define the size of the sub image, M and N define the size of the intensity image. The parameters α and β can be determined based on the mean of the darkest sub-image L_{m_min} and mean of the brightest sub image L_{m_max} as:

$$\alpha = \begin{cases} \dfrac{76.5 - L_{m\_\min}}{51} & for \quad 0 \le L_{m\_\min} \le 51 \\ 0.5 & for \quad 51 < L_{m\_\min} \le 127 \end{cases} \tag{9}$$

$$\beta = \begin{cases} \dfrac{L_{m\_\max} - 255}{51} + 1.5 & for \quad 204 \le L_{m\_\max} \le 255 \\ 0.5 & for \quad 128 \le L_{m\_\min} < 204 \end{cases} \tag{10}$$

A dark image can be determined as an image which has no bright sub image (i.e. $L_{m\_\max}$ is less than 127) and a bright image can be determined as an image which has no dark sub-image (i.e. $L_{m\_\min}$ is more than 127) For these images the shapes of the curves are adjusted according to the value of the image's global mean as:

$$\alpha = \frac{127 - I_m}{63.5} + 1.5 \qquad for\ L_{m\_\max} < 127 \tag{11}$$

$$\beta = \frac{I_m - 128}{63.5} + 1.5 \qquad for\ L_{m\_\min} > 127 \tag{12}$$

Where I_m is the global mean of the image. For some type of images, it is desired to pull up and pull down the illuminations very much at the same time, but at the expense of color consistency. In this situation, the shapes of the curves can be adjusted manually. In Fig.2, the shape of the curve for very dark images obtained by $\beta = 0.5$ and α is tuned with respect to the global mean of the image, and shape of the curve for very bright image with $\alpha = 0.5$ and β is tuned according to the global mean of the image.

Combination of Enhanced-Illumination and Reflectance. The visually significant image features (high frequency components) are combined with enhanced

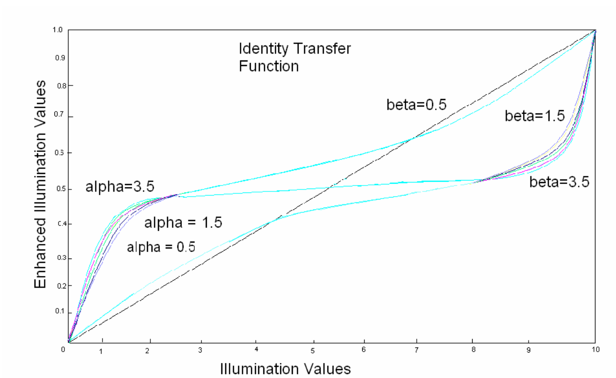


Fig. 2. Various curves of MWIS transfer function

illumination to obtain illumination and reflectance components during contrast enhancement.

$$I_{enh}(x, y) = L''_{enh}(x, y)R(x, y) \tag{13}$$

During this process, a few bright pixels which are surrounded by dark pixels leave out the range [0 1].

2.2 Contrast Enhancement

A surrounding pixel-dependent contrast enhancement technique is used to obtain sufficient contrast, even higher than that of the original image.

Obtaining Intensity Information of Surrounding Pixels. For a $M \times N$ intensity image, 2D discrete spatial convolution with a Gaussian kernel is used to obtain the intensity information of surrounding pixels and is expressed as

$$I_{conv}(x, y) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} I(m, n)F(m + x, n + y) \tag{14}$$

Where Gaussian function can be obtained as

$$F(x, y) = K \exp\left(-\frac{(x + y)^2}{c^2}\right) \tag{15}$$

Where $K = \iint F(x, y)dxdy = 1$ and c is the scale or Gaussian surround space constant which determines the size of the neighborhood.

Intensity Transformation Process. Surrounding intensity information is compared with the intensity value of the center pixel and the result is used to identify the value of corresponding enhanced intensity pixel by

$$S(x, y) = 255 \times I_{enh}(x, y)^{E(x,y)} \tag{16}$$

where $S(x, y)$ is the pixel intensity value after contrast enhancement and $E(x, y)$ is the ratio of the surrounding intensity information over input image,

$$E(x, y) = \left[\frac{I_{conv}(x, y)}{I(x, y)}\right]^P \tag{17}$$

2.3 Color Restoration

In the MWISE algorithm, a basic linear color restoration process based on the chromatic information of the input image is applied. This process can be expressed as

$$S_j(x, y) = S(x, y)\frac{I_j(x, y)}{I(x, y)} \tag{18}$$

where j = r, g, b represents red, green, blue spectral band respectively.

3 Experimental Results and Discussion

The MWIS algorithm was applied to process a large number of images consisting of very dark and bright parts. The main beneficial point of the MWISE algorithm over MSRCR, LDNE, AINDANE and IRME is the enhancement of the overexposed regions. In Fig.3 the image is composed of only bright regions. For this type of images, curvature of the second inverse sigmoid is large. In Fig.4 the image is composed of only dark regions. For this type of images, curvature of first inverse sigmoid is large. MWISE is also tested on daylight images (Fig.5) that do not have extremely dark and bright regions. While most of the images are well enhanced, some type of images that have mostly blue-sky turns to gray. The brightness of the sky misguides the parameter β, so the curve of the second inverse sigmoid function shapes more than required.

(a) (b) (c)

Fig. 3. Image under "over illumination"; (a)Original image; (b) Enhanced image with $\alpha = 0.5$ and $\beta = 1.5$; (c) Enhanced image with $\alpha = 0.5$ and $\beta = 3.5$

(a) (b) (c)

Fig. 4. Image under "low illumination"; (a) Original image; (b) Enhanced image with $\alpha = 1.4020$ and $\beta = 0.5$; (c) Enhanced image with $\alpha = 3.5$ and $\beta = 0.5$

In Figure 6, a sample image is processed for comparison among the performancesof the MWISE, MSRCR, AINDANE, and IRME techniques. The original image in Fig. 6(a) has some overexposed regions near the lamp and some

(a) (b) (c)

Fig. 5. Image on "daylight"; (a) Original image; (b) Enhanced image with $\alpha = 1.28$ and $\beta = 1.3627$; (c) Enhanced image with $\alpha = 1.28$ and $\beta = 0.5$

dark regions at the corners. The enhancement result with MSRCR introduced unnatural color or artifacts in dark areas as illustrated in Fig. 6(b). Also, the bright region near the lamp still cannot be seen. It can be observed that the images processed with AINDANE (Fig. 6(c)) and IRME (Fig. 6(d)) have a higher visual quality than those processed by MSRCR. They yield higher color accuracy and a better balance between the luminance and the contrast across the whole image. But, they are not sufficient to enhance overexposed regions. The result of the proposed algorithm is illustrated in Fig. 6(e). MWISE produced sufficient luminance enhancement in both dark and bright regions and also demonstrate high contrast, since it has flexibility and adaptiveness of AINDANE and IRME. Another comparison among these algorithms is also performed on different sample image shown in Fig. 7(a). Figures 7(b), 7(c), 7(d) and 7(e) illustrate the enhancement results of MSRCR, AINDANE, IRME and MWISE algorithms, respectively. All of the algorithms performed well for dark regions. MSRCR has lack of good contrast for this image. MSRCR and AINDANE did not perform well on overexposed regions (middle region of the hurricane). For this image, although IRME has the capability to enhance bright region due to the shape of the transfer function, the contrast of bright region is not sufficient.

3.1 Quantitative Evaluation

The visibility in original images and enhanced images are evaluated by using a statistical method [16], which is a connection between numerical and visual representations. A large number of images are tested over this statistical method. The evaluation of different images and their corresponding enhanced images are plotted (in Fig.8). The points, which are expressed with squares, represent the original images and the points, which are expressed with circles, represent the enhanced images.

Effects of the MWISE algorithm are depicted by transferring images towards the visually optimal region (rectangle). Since the original images had very dark and/or very bright properties, the enhanced images have not moved inside the visually optimal region, but they are moving towards this region.

(a) Original image

(b) Enhanced image with MSRCR

(c) Enhanced image with AINDANE

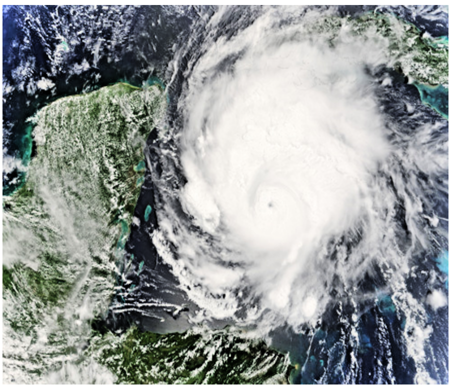
(d) Enhanced image with IRME

(e) Enhanced image with MWIS algorithm (α =0.8, β=2)

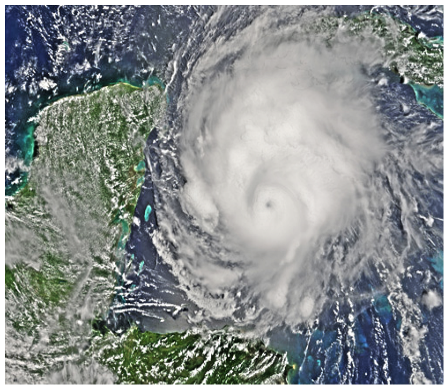
Fig. 6. Performance comparisons of the proposed technique

(a) Original image

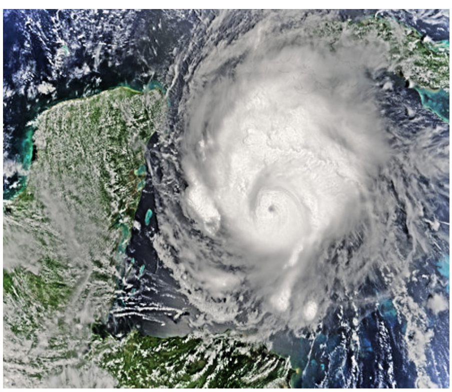
(b) Enhanced image with MSRCR



(c) Enhanced image with AINDANE



(d) Enhanced image with IRME



(e) Enhanced image with MWIS algorithm((α =1, β=1.5)

Fig. 7. Performance comparisons of the proposed technique

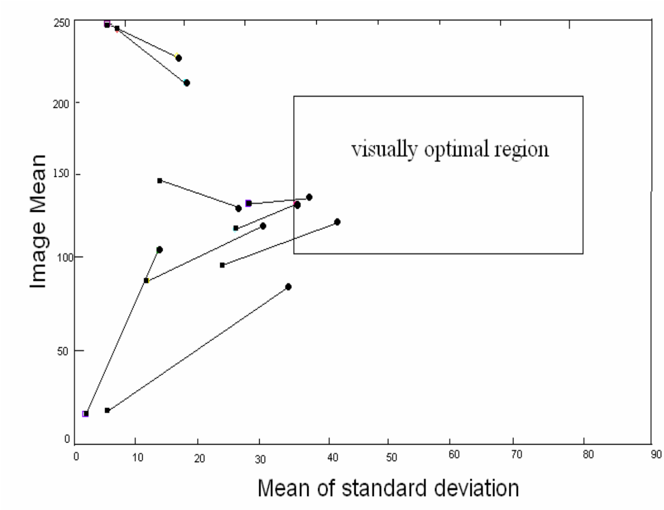


Fig. 8. Image quality evaluations

4 Conclusion

A new image enhancement algorithm for extremely non- uniform lighting images based on a multilevel windowed inverse sigmoid transfer function has been presented in this paper. The intensity enhancement, contrast enhancement and color restoration issues were considered separately to make the algorithm more adaptable to image characteristics. The input intensity image was separated into the illumination and reflectance components preserving the important features of the image. The adaptive ness of the transfer function, depending on the statistical information of the input image and its sub images, makes the algorithm more flexible and easier to control. To reduce the halo effects in bright regions, neighborhood average of illumination and intensity for bright regions was used as estimated illumination. It is observed that the MWISE algorithm yields visually optimal results on images captured under extremely non uniform lighting conditions. This algorithm would be a promising image enhancement technique that can be useful in further image analysis for pattern recognition applications.

References

1. E. Land, "Recent advances in retinex theory," *Vision Res.,* vol.16, pp.445-458, 1976.
2. D. Jabson, Z. Rahman, and G. A. Woodel, "Properties and performance of a center/surround retinex," *IEEE Trans. on Image Processing: Special Issue on Color Processing 6,* pp.451-462, March 1997.
3. Z. Rahman, D. Jabson, and G. A. Woodel, "Multiscale retinex for color image enhancement," *Proc.IEEE Int. Conf. on Image Processing*, 1996

4. Z. Rahman, D. Jabson, and G. A. Woodel, “Multiscale retinex for color rendition and dynamic range compression,” *Applications of Digital Image Processing XIX*, A.G.Tescher, Ed., *Proc.SPIE* 2847, pp.183-191, 1996.
5. L. Tao and V. K. Asari, "Modified luminance based MSR for fast and efficient image enhancement," Proc. *IEEE Int. Workshop on Applied Imagery and Pattern Recognition, AIPR - 2003*, pp. 174-179, October 2003.
6. L. Tao and K. V. Asari, “An adaptive and integrated neighborhood dependent approach for nonlinear enhancement of color images,” *SPIE Journal of Electronic Imaging,* vol. 14, no. 4, pp. 1.1-1.14, October 2005.
7. L. Tao, R. C. Tompkins, and K. V. Asari, “An illuminance-reflectance model for nonlinear enhancement of video stream for homeland security applications,” Proc. *IEEE Int. Workshop on Applied Imagery and Pattern Recognition, AIPR - 2005*, Washington DC, October 19 - 21, 2005.
8. M. Ashikhmin, “A tone mapping algorithm for high contrast images,” *Proc. Eurographics Workshop on Rendering*, pp. 145-156, 2002.
9. F. Drago, K. Martens, T. Annen, and N. Chiba, “Adaptive logarithmic mapping for displaying high contrast scenes,” *Proc. Eurographics*, 2003.
10. G. W. Larson, H. Rushmeier, and C. Piatko, “A visibility matching tone reproduction operator for high dynamic range scenes,” *IEEE Trans. Visualization and Computer Graphics,* 3(4), pp.291-306, 1997.
11. K. Chiu, M. Herf, P. Shirley, S. Swamy, C. Wang, and K. Zimmerman, “Spatially nonuniform scaling functions for high contrast images,” *Graphics Interface*, pp.245-255, May 1993.
12. C. Schlick, “Quantization techniques for visualization of high dynamic range pictures,” *5th Eurographics Workshop on Rendering*, June 1994.
13. S. N. Pattanaik, J. A. Ferwarda, M. D. Fairchild, and D. P. Greenberg, “A multiscale model of adaptation and spatial vision for realistic image display,” *Proc. SIGGRAPH 98, Computer Graphics Proc., Annual Conference Series,* pp.287-298, July 1998.
14. J. Tumblin, G. Turk, “LCIS: A boundary hierarchy for detail-preserving contrast reduction,” *Proc. SIGGRAPH 99*, pp.83-90, 1999.
15. R. Fattal, D. Lischinski, and M. Werman, “Gradient domain high dynamic range compression,” *Proc. ACM SIGGRAPH 02*, ACM Press, pp. 249-256, 2002.
16. D. J. Jabson, Z. Rahman, G. A. Woodell, “Statistics of visual representation,” *Proc. SPIE*, vol. 4736, pp. 25-35, 2002.