Rendering non-pictorial (Scientific) high dynamic range images

Sung Ho Park

Follow this and additional works at: https://repository.rit.edu/theses

Recommended Citation

This Thesis is brought to you for free and open access by the RIT Libraries. For more information, please contact repository@rit.edu.
Rendering Non-Pictorial (Scientific) High Dynamic Range Images

Sung Ho Park

B.S. Rochester Institute of Technology (1999)

A thesis submitted in partial fulfillment of the requirements
For the degree of Master of Science in Color Science
In the Center for Imaging Science,
Rochester Institute of Technology

August 2004

Signature of the Author

Accepted by Dr. Roy S. Berns,
Coordinator, M.S. Degree Program
The M.S. Degree Thesis of Sung Ho Park
has been examined and approved by two members of the
Color Science faculty as satisfactory for the thesis
requirement for the Master of Science degree

Dr. Ethan Montag, Thesis Advisor

Dr. Mark Fairchild
I, Sung Ho Park, hereby grant permission to the Wallace Memorial Library of R.I.T. to reproduce my thesis in whole or part. Any reproduction will not be for commercial use or profit.

Signature of the Author

Date
Rendering Non-Pictorial (Scientific) High-Dynamic-Range Images

Sung Ho Park

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Color Science in the Center for Imaging Science, Rochester Institute of Technology

ABSTRACT

In recent years, the graphics community is seeing an increasing demand for the capture and usage of high-dynamic-range (HDR) images. Since the production of HDR imagery is not solely the domain of the visualization of real life or computer generated scenes, novel techniques are also required for imagery captured from non-visual sources such as remote sensing, medical imaging, astronomical imaging, etc. This research proposes to integrate the techniques used for the display of high-dynamic-range pictorial imagery for the practical visualization of non-pictorial (scientific) imagery for data mining and interpretation.

Nine algorithms were utilized to overcome the problem associated with rendering the high-dynamic-range image data to low-dynamic-range display devices, and the results were evaluated using a psychophysical experiment. Two paired-comparison experiments and a target detection experiment were performed. Paired-comparison results indicate that the Zone System performs the best on average and the Local Color Correction method performs the worst. The results show that the performance of different encoding schemes depend on the type of data being visualized. The correlation between the preference and scientific usefulness judgments ($R^2 = 0.31$) demonstrates that observers tend to use different criteria when judging the scientific usefulness versus image preference. The experiment was conducted using observers with expertise (Radiologists) for the Medical image to further elucidate the success of HDR rendering on these data. The results indicated that both Radiologists and Non-radiologists tend to use similar criteria regardless of their experience and expertise when judging the usefulness of rendered images. A target detection experiment was conducted to measure the detectability of an embedded noise target in the Medical image to demonstrate the effect of the tone mapping operators on target detection. The result of the target detection experiment illustrated that the detectability of targets the image is greatly influenced by the rendering algorithm due to the inherent differences in tone mapping among the algorithms.
ACKNOWLEDGEMENTS

I am sincerely thankful to all the people who have given me support and guidance in completion of this thesis. My sincerest thanks go to:

Dr. Ethan Montag, my advisor, for his guidance, support, and understanding,

My lovely wife, Kyung Hyun Kim, and my parents for their endless love, encouragement, support, and friendship,

The MCSL family, especially Dr. Mark Fairchild, Dr. Roy Berns, Dr. Noboru Ohta, Dr. Mitch Rosen, Dr. Garrett Johnson, Lawrence Taplin, Dave Wyble, Collen Desimone, and Valerie Hemink for their support, guidance, and ruthless homework's during my time here at MCSL as a graduate student. It has been a truly wonderful, enjoyable, and unforgettable experience.

All the observers who participated in the psychophysical experiments for their time and support. Especially, Dr. Ethan Montag for completing the long tedious target detection experiment.

All the friends and colleagues; Rohit Patil, Hasegawa (Hase) Takayuki, Erin Murphy, Xiaoyan (Yan) Song, Chengmeng Liu, Jiangtao (Willy) Kuang, Yongda Chen, Hongqin (Cathy) Zhang, Justin Laird, Mahdi Nezamabadi, etc., for their support and friendship over the past two years.
TABLE OF CONTENTS

TABLE OF CONTENTS ................................................................. I
LIST OF TABLES ................................................................. III
LIST OF FIGURES ................................................................. IV
LIST OF EQUATIONS ............................................................... VII

1. INTRODUCTION .......................................................... 1

2. BACKGROUND .............................................................. 5
   2.1. Overview .............................................................. 5
   2.2. Duplicity Theory and Spectral Sensitivity of HVS ....................... 8
   2.3. Threshold Sensitivity ............................................... 13
   2.4. Time Course of Adaptation ....................................... 17
       2.4.1. Light adaptation ............................................ 17
       2.4.2. Dark adaptation ............................................. 19
   2.5. The Contrast Sensitivity Function ................................ 21
   2.6. Multiple Spatial Frequency Channels ............................... 25
   2.7. Spatial Summation .................................................. 27
   2.8. Suprathreshold Vision .............................................. 28
   2.9. Summary ............................................................. 31

3. REVIEW OF TONE REPRODUCTION OPERATORS .................... 32
   3.1. Spatially Uniform Operators .................................... 35
   3.2. Spatially Varying Operators .................................... 42
LIST OF TABLES

Table 1    Information of the imagery exploited in the study...................... 61
Table 2    Goodness-of-fit test for paired-comparison experiments.................. 78
Table 3    Results of target detection experiment...................................... 90
LIST OF FIGURES

Figure 1  The dynamic range of the visual system................................. 7
Figure 2  Simulation of visual function across a wide range of luminance........ 9
Figure 3  The CIE relative luminous efficiency function: scotopic (rod) $V'_\lambda$ and
photopic (cone) $V_\lambda$ luminous efficiency function........................................ 10
Figure 4  Changes in the spectral sensitivity of rod and cone system; (a) scotopic, (b)
mesopic, and (c) photopic illumination levels...................................................... 11
Figure 5  Changes in the spectral sensitivity as a function of background luminance for
the rod and cone...................................................................................................... 13
Figure 6  Threshold vs. intensity (t.v.i) functions for the rod and cone system over the
full range of vision..................................................................................................... 14
Figure 7  Threshold vs. intensity (t.v.i) function for the rod system...................... 15
Figure 8  The time course of light adaptation in the cone system......................... 18
Figure 9  The time course of light adaptation in the rod system........................... 19
Figure 10 The time course of dark adaptation....................................................... 20
Figure 11 Contrast sensitivity as a function of spatial frequency at different mean
luminance levels....................................................................................................... 23
Figure 12 The contrast sensitivity function plotted against mean luminance. Contrast
thresholds are shown for gratings of nine different spatial frequencies
indicated on the right. The slope of -0.5 portion of line indicates de Vries-
Rose law and horizontal portion of line represents Weber's law.................. 24
Figure 13  Multiscale bandpass mechanism underlying the contrast sensitivity functions ................................................................. 26

Figure 14  Thresholds as a function of circular increments of various sizes and duration either 8.5 or 930 ms ................................................................. 27

Figure 15  Suprathreshold contrast constancy ................................................................. 29

Figure 16  Ideal tone reproduction process ................................................................. 32

Figure 17  Categorization of Tone Reproduction Operators ................................................................. 34

Figure 18  Stevens’ model of suprathreshold brightness and apparent contrast ................. 36

Figure 19  The flow chart of iCAM for rendering HDR images ................................................... 56

Figure 20  Histograms and thumbnails of the imagery exploited in the study ...................... 63

Figure 21  The Medical image rendered with nine different operators ........................................ 65

Figure 22  Illustration of three different targets for target detection experiment .............. 68

Figure 23  Results of paired-comparison data for all images ................................................... 70

Figure 24  Average performance of paired-comparison experiments ........................................ 71

Figure 25  Plot of Preference vs. Scientifically Useful; shows correlation between two data ................................................................. 71

Figure 26  Schematic diagram for Astronomical and Pictorial image ........................................ 72

Figure 27  Comparison of paired-comparison experiment; Radiologist vs. Naïve .............. 73

Figure 28  Schematic diagram for Medical image ................................................................. 74

Figure 29  Plot of paired-comparison result for InfraRed image ............................................. 75

Figure 30  Comparing processed InfraRed image; Linear vs. Zone system and Linear vs. iCAM ................................................................. 75

Figure 31  Plot of paired-comparison result for Pictorial image ............................................. 76
Figure 32  The dual scaling results for the preference experiment..................80
Figure 33  The variance plots for dual scaling results for the preference experiment...81
Figure 34  Dual scaling results for the scientific usefulness experiment...............83
Figure 35  The variance plots for dual scaling results for the scientific usefulness experiment.................................................................84
Figure 36  The dual scaling result and the corresponding variance plot of the Radiologists’ data.................................................................86
Figure 37  The dual scaling result and the corresponding variance plot for the data combing Radiologists’ data and Non-radiologists’ data.........................87
Figure 38  Plots of Probit analysis for the iCAM.....................................................89
Figure 39  Bar graph of target detection experiment results...............................91
# List of Equations

<table>
<thead>
<tr>
<th>Equation</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equation 1</td>
<td>The form of the sigmoid functions was derived from a discrete cumulative normal function.</td>
<td>50</td>
</tr>
<tr>
<td>Equation 2</td>
<td>The Gaussian filter used for acquiring the low-pass version of the image.</td>
<td>52</td>
</tr>
<tr>
<td>Equation 3</td>
<td>The local color correction function that performs a pixel-by-pixel gamma correction.</td>
<td>54</td>
</tr>
<tr>
<td>Equation 4</td>
<td>Computing input scaling factor for iCAM.</td>
<td>55</td>
</tr>
<tr>
<td>Equation 5</td>
<td>Bilateral filter used for compressing the contrast of the base layer.</td>
<td>58</td>
</tr>
<tr>
<td>Equation 6</td>
<td>Blommaert’s model used for estimating the size of a local region by measuring local contrast.</td>
<td>59</td>
</tr>
<tr>
<td>Equation 7</td>
<td>The center-surround function in Zone System.</td>
<td>60</td>
</tr>
<tr>
<td>Equation 8</td>
<td>The local tone reproduction operator for Zone System.</td>
<td>60</td>
</tr>
</tbody>
</table>
Chapter 1

INTRODUCTION

One possible aim of realistic image rendering or reproduction is the creation of images that share identical appearance attributes as a real scene. The real world exhibits a wide range of luminance values. The human visual system is capable of perceiving this wide range of dynamic scenes spanning five orders of magnitude and adapting more gradually to over nine orders of magnitude, which is facilitated by local adaptation that allows regions of various luminance levels to be viewed essentially simultaneously. Recent advances in high dynamic range capturing systems (Debevec \& Malik, 1997; Nayar \& Mitsunaga, 2000; Xiao et al., 2002) make it possible to capture a highly detailed range representation of the scene and later process the data in order to select the image that better fulfills the given requirements. Unfortunately, the dynamic range of image display devices and image display media have not kept up with the progress in digital image capture devices and methods. Since a typical desktop displays, such as CRTs and LCDs, are only capable of displaying two orders of magnitude of dynamic range, the question is then how can we reproduce and visualize such HDR images in a standard output device. This is fundamentally possible because the human eye is sensitive to relative luminance values, rather than absolute luminance.

More recently, concern has grown in the visualization and scientific communities over the use of scientific imagery, its interpretation, and the relation of the data to its
Novel techniques are also required for imagery captured from non-visual sources such as remote sensing, medical imaging, astronomical imaging, etc. The goal of this study is to integrate the techniques used for the display of HDR pictorial imagery for the display of non-pictorial imagery while searching for perceptually based schemes for encoding this imagery that facilitate its interpretation. By applying these same HDR processing techniques developed for pictorial imagery, it is hypothesized that more information can be conveyed because local perceptual contrast in a wider range of the scene will be preserved by automatically adjusting the luminance and chromatic contrast in the image based on the image content.

Much research has been done to develop algorithms that are capable of recreating a truthful rendition of high-dynamic-range image onto lower-dynamic-range displays (Reinhard et al., 2002; Durand & Dorsey, 2002; Johnson & Fairchild; 2003). For pictorial imagery, the truthfulness or accuracy of the display lies in the ability to recreate the appearance qualities of the original scene. However, for non-pictorial imagery, the truthfulness of the display cannot be evaluated by comparison with the original scene. Instead, the usefulness of the display lies in the ability of the user to visually interpret and use the data. The term, non-pictorial, refers to scientific imagery captured outside the visible wavelength region or of objects not accessible to the human eye, such as hyperspectral data captured by spacecraft or aircraft, astronomical images captured using non-visible wavelengths, or characteristics of human tissue obtained in medical imaging. Since main focus of this project is to test algorithms for the display of non-pictorial HDR imagery that is univariate, the visualization of multidimensional data is not concerned in this study.
There are three aspects of this study: 1) The development and implementation of HDR algorithms including some used for HDR pictorial imagery. 2) The psychophysical evaluation of these algorithms in rendering this non-pictorial imagery, and 3) The psychophysical measurement of the effect of tone and contrast mapping on target detection.

The results from the evaluation aspect will be used as feedback to help improve the algorithms used to encode the data. Two psychophysical experiments were conducted to evaluate these algorithms. The goal of the psychophysical testing was to determine which algorithms were preferred and which algorithms were judged as being more scientifically useful.

Eight algorithms – Linear Mapping, Sigmoid-lightness Rescaling (Braun and Fairchild, 1999), Spiral Rendering (Montag, 1999), Photoshop (Auto-levels), iCAM (Fairchild and Johnson, 2002), Local Color Correction (Moroney, 2000), Fast Bilateral Filtering (Durand and Dorsey, 2002), and Zone System (Reinhard et al., 2002) – primarily proposed for the display of HDR pictorial imagery were implemented for the display of non-pictorial imagery. Moreover, the Localized Sigmoid function was developed based on the idea of the Sigmoid-lightness Rescaling function and extended to locally control the contrast of the HDR image using the independent sigmoid look-up-table for each pixel in the image. A total of nine algorithms were examined in this study.
Two experiments were conducted to judge both the observers' preference and the scientific usefulness of the images in a paired-comparison paradigm. The goal of the first experiment was to determine which encoding schemes rendered the high dynamic range images in more preferable way. In the second experiment, the observers were instructed to judge scientific usefulness of the image in each pair. To help further elucidate the success of HDR rendering, the experiment was extended for radiologists to evaluate the success of rendering an HDR Medical image. The results of paired-comparison data were analyzed using Thurstone's Law of Comparative Judgements (Case V) (Engeldrum, 2000). Mosteller's Chi-Square goodness-of-fit test and dual scaling analysis were also performed to examine the normality in the observed distribution of response and to find the hidden structure within a data set, respectively.

A target detection experiment was performed to measure how the change in contrast tone mapping due to the various algorithms affected the detection of a target as measured by the amplitude of the target in the raw image data. This experiment used a two-alternative forced-choice method of constant stimuli to find the threshold for detecting embedded noise target in the Medical image. The task of target detection can be considered as a way of determining the change in detectability of a "tumor" embedded in the image. The experiment was analyzed using Probit analysis to determine the corrected-for-chance 50% threshold for target detection.
Chapter 2

BACKGROUND

2.1. Overview

In our daily environment, the Human Visual System (HVS) copes with the large variations of the luminance input to the eyes through adaptation. When the eye moves around in a natural environment, the luminance input to the eyes changes continually. The sensitivity of the HVS is continually adjusted in order to allow efficient transfer of information about the visual input to the brain. Without such an adjustment, small signals will drown in neuronal noise, and large signals will saturate the system. The purpose of luminance adaptation is thus to keep the response to rapidly varying visual input within the dynamic range of the neurons in the retina (Shapley & Enroth-Cugell, 1984). These adaptation mechanisms have been studied extensively, both psychophysically (Hayhoe et al., 1992; Foley & Boynton, 1993; Kortum & Geisler, 1995; Hood et al., 1997; Poot et al., 1997) and physiologically (Lankheet et al., 1993; Wu & Burns, 1996; Yeh et al., 1996; Shapley, 1997; Victor et al., 1997). Although these studies are giving an increasingly detailed view of early processes of luminance and contrast adaptation, it is not clear how these processes act in performance under natural luminance conditions. However, enough information has been accumulated to develop computational models of initial stages of the HVS.
One of the most remarkable properties of visual system is that it adapts its properties in responses to the specific properties of the prevailing stimulus. These adjustments allow the visual system to follow and tune for the characteristics of the visual environment, and determine the capacities and limits of our perception. There are two fundamentally different forms of visual adaptation, luminance adaptation and chromatic adaptation (Barlow and Mollen, 1982; Wyszecki and Stiles, 1982; Wandell, 1995; Bartleson, 1978; Wright, 1981). Although the chromatic adaptation process is important for obtaining a complete picture of adaptation, it will not be discussed in depth in this thesis.

Luminance adaptation is the term used for the process that changes the sensitivity of the visual system to different light levels. The problem of adapting to increase and decrease in illumination is best understood by considering the variety of situations confronting the human visual system. The human observer experiences a range of naturally occurring ambient light levels of nearly 14 log units and must be able to discriminate objects in the environment over 8 log units. However, the differences in intensity reflected by those objects at any single light level are very small, spanning at best 2 to 3 log units (Walraven et al., 1990). Figure 1 illustrates the range of luminance we encounter in the natural environment and summarizes some visual parameters associated with this luminance range. The question that models of adaptation must answer is how the visual system remains sensitive to such small differences over such a wide ambient range.
Adaptation takes place at several different sites in the visual system (Hood & Finkelstein, 1986; Walraven et al., 1990). These different adaptation processes complement each other. Before light reaches the retina its intensity is already regulated by the size of the eye's aperture, the pupil. Another adaptation process is formed by the division of photoreceptors into rods and cones. The rod system is very sensitive and works mainly at low (scotopic) light levels, but it is saturated at daylight (photopic) levels when the cone system becomes active. At very high light intensities a third adaptation process becomes important, namely bleaching and regeneration of photopigment. This reduces the amount of photopigment available and thereby prevents saturation of the cone system. The pupil, the rod and cone systems, and bleaching and regeneration of receptor photopigments all play an important role in visual adaptation. Adaptation is achieved through the action of these mechanisms that is reflected in the changes in visibility, color appearance, visual acuity, and sensitivity over time that can be observed in everyday experience and measured in psychophysical experiments.
Adaptation is an ensemble of adjustments made by the HVS in response to the amount of available light in a scene. Although the visual system is sensitive over a vast range of illumination through adaptation, it does not mean that it is equally sensitive to lights of all wavelengths. Equal numbers of quanta of different wavelengths differ greatly in brightness and in detectability. Furthermore, the visual system’s relative sensitivity to lights of different wavelengths is not constant. The experiments show that threshold visibility, color appearance, and visual acuity are different at different illumination levels, and that these visual parameters change over the time-course of adaptation. The following section reviews the psychophysically documented characteristics of the adaptation process that measure the changes in visual function.

2.2. Duplicity Theory and Spectral Sensitivity of HVS

The human eye contains two types of receptors, rods and cones named after the characteristic shapes of their outer segments. The fundamental differences between rods and cones constitute the basis of duplicity theory (Gegenfurtner and Sharpe, 2001; Palmer, 1999; Boynton, 1979) and the HVS is mediated by these two receptors. The rods serve vision at low luminance levels, called scotopic levels functioning within a range of $10^{-6}$ to $10$ cd/m$^2$, while the cones serve vision at higher luminance levels, called photopic levels covering a range of $0.01$ to $10^8$ cd/m$^2$. Vision in which both rods and cones are active is called mesopic levels between $0.01$ to $10$ cd/m$^2$ (see Figure 1). Thus the transition from rod to cone vision is one mechanism that allows our visual system to function over a large range of luminance levels. The rods are extremely sensitive at low
luminance (scotopic) levels and can detect small luminance differences, however poor at discriminating details (acuity) and do not provide color discrimination. In comparison, the cones are less sensitive than the rods and luminance differences have to be large to be detectable, however they provide color vision at high luminance (photopic) levels and responsible for detection of fine detail. Figure 2 illustrate the simulation of color sensitivity and visual acuity across a wide range of luminance levels.

![Figure 2. Simulation of visual function across a wide range of luminance (Pattanaik et al., 1998)](image)

Rods and cones also differ substantially in their spectral sensitivities. A spectral sensitivity function relates sensitivity of the rod and cone systems to the wavelength of light from approximately 400 to 700 nanometers (nm). There is only one type of rod receptor with a peak spectral sensitivity at approximately 505 nm. There are three types of cone receptors with peak spectral sensitivities spaced throughout the visual spectrum – the composite cone system peaks at approximately 555 nm.
The practical importance of specifying the effectiveness of lights for vision led the CIE (Commission International de l'Eclairage) to adopt two standard spectral sensitivity (relative luminous efficiency) functions (Wyszecki and Stiles, 1982). Figure 3 illustrates these two functions: One function specifies relative sensitivity of the visual system under scotopic (rod) conditions, the other under photopic (cone) conditions with each curve normalized to a maximum log relative efficiency of 0.0. Since there is only one type of rod, the scotopic luminosity function (also called $V'_\lambda$) is identical to the spectral sensitivity of the rods. However, the photopic luminosity function (also called $V_\lambda$) represents a combination of the three types of cone signals rather than the sensitivity of any single cone type. Figure 3 also illustrates the shift in peak spectral sensitivity toward shorter wavelengths during the transition from photopic to scotopic vision. This shift, called the Purkinje shift, explains why blue objects tend to look lighter than red objects at very low luminance levels. With scotopic vision, eyes are more sensitive to shorter wavelengths.

![Figure 3. The CIE relative luminous efficiency function: scotopic (rod) $V'_\lambda$ and photopic (cone) $V_\lambda$ luminous efficiency function (Wyszecki & Stiles, 1982)](image-url)
The scotopic and photopic luminosity functions represent the overall sensitivity of the two systems (rod and cone) with respect to the perceived brightness of the various wavelengths operating over different luminance ranges and constructing a model of visual sensitivity. Although, in reality, the shape of luminosity function changes with adaptation – particularly conditions of chromatic adaptation, each system is assumed to have an invariant relative spectral sensitivity (Stockman and Shape, 1999). Changes in parameters such as adapting intensity or the retinal position of the stimulus change the absolute sensitivity of a system but not its relative sensitivity to lights of different wavelengths. The systems are also assumed to be independent; the sensitivity of one system is unaffected by stimulation of the other (Stiles, 1959). The system more sensitive to a particular luminance level determines the overall sensitivity of the visual system to that luminance. The independence assumption leads to the prediction that the overall spectral sensitivity will approximate an envelope of the component rod and cone system sensitivities. Changes in the shape of the overall sensitivity curve that occur with variations in different luminance levels reflect changes in relative sensitivity between systems, never within systems.

Figure 4. Changes in the spectral sensitivity of rod (dashed line) and cone (solid line) system (Hood & Finkelstein, 1990); (a) scotopic, (b) mesopic, and (c) photopic illumination levels.
Figure 4 graphically shows the changes in relative sensitivity between systems that corresponds to a differential shifting of the scotopic and photopic functions vertically along the log sensitivity axis at different luminance levels as using a constant chromaticity of the illuminant; the visual system’s spectral sensitivity at (a) scotopic, (b) mesopic, and (c) photopic levels. In Figure 4 (a), the rod system is more sensitive at all wavelengths and alone determines overall sensitivity. Since the rod system is very sensitive at scotopic levels, absolute sensitivity is high, but color information will not be provided because of achromatic nature of the rod system. Conversely, in Figure 4 (c), overall sensitivity is dominated by the cone system at photopic levels. The sensitivity of the cone system exceeds that of the rod system over the entire spectrum. Absolute sensitivity has dropped considerably, but due to the trichromatic nature of the cone system, colors will be apparent. Figure 4 (b) illustrates mesopic levels situation. Rod system controls sensitivity to wavelengths below about 580 nm and cone system determines sensitivity above this point. Sensitivity at a particular wavelength is managed by the more sensitive system. Figure 5 shows 3D representation of Figure 4 providing clear demonstration of how the visual system’s spectral sensitivity varies with changing luminance levels and which system is dominant at a particular level.
2.3. Threshold Sensitivity

The effect of adaptation on visual sensitivity is often measured psychophysically in a detection threshold experiments. The term sensitivity is defined as the reciprocal of the minimum stimulus strength required for the stimulus to be reliably detected (1/threshold) and thus, simply, the visual system’s ability to discriminate small changes in stimulus strength. A threshold-versus-intensity (t.v.i) function is probably the most frequently used characteristic for studying adaptation processes (Blackwell 1946 & 1972). Figure 6 shows the psychophysically measured t.v.i function for the rod and cone systems that accompanies with changes in the level of illumination. As the background luminance increases, the rod system loses sensitivity and the detection threshold rises, moreover, visual function shifts from domination by the rod system to domination by the cone system. Figure 7 shows the scotopic t.v.i function obtained under experimental conditions of Aguilar and Stiles (1954; Davson, 1990).
Figure 6. Threshold vs. intensity (t.v.i) functions for the rod and cone system over the full range of vision (Pattanaik, 1998)

Figure 7 indicates that the curve remains constant and equal to the absolute threshold at luminance levels below about -4 log cd/m². Sensitivity in this section is limited by neural noise called “dark light”. The background is relatively low and dose not significantly affect threshold which approaches the limit for detecting a stimulus in the dark (the absolute threshold). The second part of the curve is called the de Vries-Rose law region (Rose, 1948). This part of the curve is limited by the fluctuations of the background noise. Threshold increases with background luminance. The visual system adjusts sensitivity in proportion to the square root of the background luminance, the slope of one half in a log-log plot.
Over a wide middle range covering approximately 3.5 log units of background luminance, the size of the threshold increment increases in proportion to the background luminance making the functions linear on a log-log scale. This linear relationship is known as Weber's law. This section of the curve demonstrates an important aspect of the visual system. The visual system is designed to distinguish objects from its background. In the real world, objects have contrast, which is constant and independent of ambient luminance. Therefore, the principle of Weber's law can be applied to contrast which remains constant regardless of illumination changes. This is called contrast constancy (or contrast invariance) with this contrast level defined as Weber constant. Contrast constancy can be mathematically expressed as $\Delta L/L = \text{constant}$. $\Delta L$ is the increment threshold on a background $L$. The constant is also known as the Weber constant or Weber fraction.
The last section of the curve shows rod saturation at high background luminance above 2 log cd/m². The slope begins to increase rapidly and the rod system starts to become unable to detect the stimulus. This rod saturation might be advantageous because it effectively prohibits the rod system from interfering with the signal processing of the cone system. The mechanism that might protect the rods from response saturation is bleaching of the photopigment. However, due to their high sensitivity, the rods already reach their maximum response at light levels that produce negligible bleaching.

The other curve shown in Figure 6 represents the t.v.i. function for the cone system that shows the similar pattern of response. At the luminance of background levels below about -2.6 log cd/m², the cones are operating at their absolute levels of sensitivity and the background has no effect on the threshold. The linear portion of the curve at background levels above 2 log cd/m² indicate Weber's law behavior and constant contrast sensitivity as discussed above. One major difference between the rod and cone functions is that the cone system never saturates in the higher luminance range. Photopigment bleaching increases in proportion with intensity and, thus, by actually bringing the effective photon catch to a standstill, enables the cones to operate indefinitely to damaging intensity levels (Walraven et al, 1990).
2.4. The Time-Course of Adaptation

When humans are viewing an environment, the way that this is perceived is greatly affected by the luminance in the scene. When going from a bright environment to a dark one (and vice versa) the scene that we perceive can have a very different visual appearance. This phenomenon is known as adaptation. However, this process is time dependent and can vary from a few seconds to several minutes. Adaptation does not happen instantaneously.

2.4.1. Light adaptation

The visual system becomes adapted to increase in illumination when going from dark lecture room to sunny outside. This process is known as light adaptation. The bright light momentarily dazzles the eye and it is difficult to see for several seconds before the eye adjust to the new level of illumination. Since the sensitivity of the eye is set to dim light, rods and cones are both stimulated and large amount of the photopigment are broken down instantaneously, producing a flood of signals resulting in the glare. Light adaptation is accompanied by the bleaching of photopigment. As light is absorbed by the photopigment, increased bleaching reduces the signals to the brain thereby adjusting sensitivity.
Figure 8 shows how threshold varies for the time course of light adaptation in the cone system at a 3.75 log cd/m² (see Baker, 1949 for more detail). Thresholds are highest immediately after the onset of the adapting field and decrease with continued exposure. The threshold drop to about 2.9 log cd/m² reaching a minimum after approximately 3 minutes and then rise slightly due to interactions between neural and photochemical processes in adaptation (particularly at the highest adapting intensity). The adjustment in sensitivity can be rapid for low adapting field but can require more than 10 minutes to reach its fully adapted level for the more intense fields (Hood & Finkelstein, 1986).
The rods threshold for the time course of adaptation at a background field of 0.5 log cd/m² is shown in Figure 9 which indicates a similar recovery function (Adelson, 1982). The light adaptation in the scotopic range of the rod system is extremely rapid. Threshold is highest at the onset of the background and decreases rapidly within the first 200 msec followed by more gradual recovery of sensitivity within the first 2 second and lasting through the first minute of adaptation. The time course of light adaptation in the rod system occurs faster than the cone system.

2.4.2. Dark adaptation

Dark adaptation is essentially the reverse of light adaptation. It can be experienced when going from a well lighted area to a dark area. Initially blackness is seen because the cones cease functioning in low intensity light. Also, much of the rod pigments has been bleached out due to the bright light and the rods are initially nonfunctional. Once in the
dark, the rod photopigment (rhodopsin) regenerates and the sensitivity increases over time (Davson, 1990). One of the major differences between dark adaptation and light adaptation is their time course. While dark adaptation takes nearly 40 minutes to be complete, light adaptation happens very rapidly, usually in less than a minute. Another difference is that when dark adapted, momentarily blindness may be experienced because of the slow process of regeneration of photopigment. However, for the light adaptation, the temporarily blindness does not occur. At first everything is painfully glaring because of high sensitivity. As the system quickly adapts, the sensitivity decreases and normal vision is restored.

![Figure 10. The time course of dark adaptation (Ferwerda et al., 1996).](image)

The time course of dark adaptation curve shown in Figure 10 depicts the duplicity theory of visual system by two branches (Hecht, 1934; Crawford, 1947; Hood & Finkelstein, 1986). These two branches are due to the transition from the cone to the rod system, each
of which has a different time course of adaptation. The cone system recovers sensitivity much more quickly than does the rod system, but the absolute sensitivity of the rod system is much greater. The initial rapid drop followed by slow decline of threshold curve in Figure 10 reflects the cone system. The full recovery of cone sensitivity is completed within 8 minutes. After about 7 minutes in the dark the sensitivity of the rod system improves considerably and the threshold begin to decrease again, but, in slower rate. The curve reaches to a minimum absolute threshold at about $10^{-5}$ cd/m$^2$ after about 40 minutes in the dark.

2.5. The Contrast Sensitivity Function

Spatial vision refers to the visual system’s ability to resolve or discriminate spatially defined feature that transform the light patterns into the colors, sizes, shapes, locations, and motions of the objects we perceive in the world around us. In this regard, contrast is an important parameter in assessing vision. In reality, objects and their surroundings are of varying contrast. Therefore, the relationship between visual acuity and contrast allows a more detailed understanding of the visual perception.

The contrast sensitivity function (CSF) provides a comprehensive test of spatial vision and can be considered as a spatial frequency response of human vision (Laming, 1991a). The CSF characterizes the ease with which visual system is able to detect objects of various sizes and perceive the structural detail of objects. Conditions that alter the CSF, such as luminance level, change the visibility and appearance of objects (Olzak &
Thomas, 1990). The CSF is defined as the sensitivity versus spatial frequency, where sensitivity is measured as the reciprocal of the minimum visible contrast of sinusoidal grating stimuli. The sensitivity is measured at widely varied spatial frequency in cycles per degree of visual angle to define a CSF curve that is plotted on log sensitivity versus log frequency. Contrast is normally defined using the Michelson definition of contrast: 
\[
(L_{\text{max}} - L_{\text{min}})/(L_{\text{max}} + L_{\text{min}}),
\]
where \(L_{\text{max}}\) is the maximum luminance of the grating, and \(L_{\text{min}}\) is the minimum luminance of the grating.

The general shape of CSF is that of band-pass filter, characterized by a peak in the middle-frequency range with a sharp decline at higher spatial frequencies, and a more gradual fall-off at lower spatial frequencies. The low spatial frequency fall-off is generally accepted to reflect lateral inhibitory processes in the visual system, while the high spatial frequency decrease has been ascribed entirely to optical and receptoral factors (Banks et al., 1987). Figure 11 shows the contrast sensitivity of the visual system based on van Nes’ empirical model (van Nes & Bouman, 1967). Each curve in the figure show the change in contrast sensitivity for sinusoidal gratings modulated around mean luminance levels ranging from 0.0009 to 900 td (troland). The peak of the CSF depends upon mean luminance, but generally occurs in the range of 4 to 8 c/deg. The high-frequency cut-off at high luminance level may be extrapolated to represent the acuity, or limit of spatial resolution, for a grating stimulus which lies between 50 to 60 c/deg.
Contrast sensitivity function changes shape and the location of the peak shifts to lower spatial frequencies as mean luminance decreases. In other words, as the mean luminance changes from photopic to scotopic levels, the contrast sensitivity to medium and high spatial frequencies decreases, so the curves become less peaked and shift downwards and to the left. The contrast sensitivity is reduced with decreased luminance and the shape of the CSF changes from band-pass to low-pass. This result is clearly shown by the multiple curves in Figure 11. Another change occurring with decreases in mean luminance is that the resolution capabilities of the visual system decrease. The high-frequency cut-off (acuity) occurs at lower spatial frequencies.
Figure 12. The contrast sensitivity function plotted against mean luminance (Laming, 1991a). Contrast thresholds are shown for gratings of nine different spatial frequencies indicated on the right. The slope of -0.5 portion of line indicates de Vries-Rose law and horizontal portion of line represents Weber’s law.

As the mean luminance changes from the photopic to the mesopic range, the contrast sensitivity to medium and high spatial frequencies decreases, but the sensitivity to low spatial frequencies is relatively unaffected. As evident in Figure 11, where these curves converge and overlap, the contrast sensitivity is constant despite the change in mean luminance. This is where Weber’s law holds (Laming, 1986 & 1991a). As the mean luminance moves to the scotopic range, the contrast sensitivity decreases dramatically for all spatial frequencies, following the square-root law (also known as the de Vries-Rose law). The square-root relation between contrast threshold and mean luminance at the scotopic to the mesopic range has been verified by Hess and Nordby (1986). Figure 12 shows the same data as Figure 11, but with the contrast threshold plotted against mean luminance to more clearly illustrate the relationship. The plots consist of two straight line segments. At low luminances, the contrast sensitivity decreases following the square-root of the luminance, the straight line with a gradient of -0.5 representing this de Vries-Rose
law. The square-root law is usually considered to be a result of photon noise becoming significant at low luminance levels. At high luminances, on the other hand, a constant contrast threshold caused by linear relationship between the increment threshold and the background intensity is observed following the Weber’s law, representing the horizontal line, where contrast sensitivity is constant as mean level changes, in Figure 12. The transition from the Weber range to the de Vries-Rose range occurs at lower luminances for lower frequencies (see Laming, 1986 for more detail).

2.6. Multiple Spatial Frequency Channels

Psychophysical, physiological, and anatomical evidence suggest that the early stages of visual processing can be described as filtering mechanisms that contains groups of independent band-pass filters, each of which is more narrowly tuned for spatial frequency than the overall CSF. These multiple mechanisms are sensitive to different scale and different ranges of spatial frequencies. The CSF, then, represents not the sensitivity of a single typical visual channel or cell, but the envelope of the sensitivity of all these narrowly tuned multiple channels as shown in Figure 13 (De Valois & De Valois, 1990).

The idea is that the visual system analyzes the visual scene in terms of multiple channels, each sensitive to a different preferred spatial frequency that responds over only a limited range of frequencies and a different maximum sensitivity of each channel. Moreover, the scene is also decomposed into channels sensitive to narrow bands of orientation.
Psychophysical evidence of this multi-channel concept indicates that these band-pass mechanisms adapt to the average luminance within a region of a scene defined by their spatial scale and frequency. In a complex scene, the average luminance differs at different scales reflecting different states of adaptation for the mechanisms. In order to correctly account for the changes in visual sensitivity that occur with changes in the level of illumination, visual models of spatial vision should describe the effects of local adaptation not only spatially within different regions of the visual field, but also in terms of the scale and spatial frequency filtering characteristics of the band-pass mechanisms involved in early visual processing. This concept of multi-channel representations forms the basis of many models of spatial vision and pattern sensitivity.
2.7. Spatial Summation

The basic data that describe sensitivity to spatially localized stimuli are spatial summation curves, which relate the luminance threshold to stimulus size. Each curve in Figure 14 illustrates the contrast threshold for circular spots of light as a function of stimulus size and duration (Laming, 1991b). The contrast threshold of each curve is lower for larger stimuli than for small, reflecting the property termed spatial summation.

![Figure 14. Thresholds as a function of circular increments of various sizes and duration either 8.5 or 930 ms (Laming, 1991b).](image)

The continuous straight lines in the Figure 14 represent complete spatial summation, which obtains up to a certain minimum area. Such complete summation is described by Ricco's law, which characterizes integration across space as the linear sum of the light within a stimulus (Davson, 1990). According to Ricco's law, threshold is reached when...
the total luminous energy reaching a constant value. Threshold is reached when the product of luminance and stimulus area equals or exceeds this constant value. In other words, when luminance is halved, a doubling in stimulus area is required to reach threshold. When luminance is doubled, the stimulus area can be halved and still reach threshold. The dotted line represents where this linear relationship breaks down, and the point at where the Ricco’s law breaks down is called the critical diameter. Beyond the critical diameter, the threshold contrast decreases more slowly than Ricco’s law predicts, indicating only partial summation across space. The critical area is larger for low luminance and smaller for high luminance. Such a change reflects the functional alteration of receptive field size with changes in adaptation level (Shapley and Enroth-Cugell, 1984).

2.8. Suprathreshold Vision

The discussion so far has focused on threshold measurements of contrast. The visual sensitivity to contrast at threshold is very dependent on spatial frequency and has been studied in-depth to understand the limits of visual perception. Although the threshold models of vision have offered enormously useful information on the limits of visibility that have luminance variation over space and time, they don’t provide the relationship between the perception of contrast and spatial frequency at levels well above threshold. Most of the external visual world is at suprathreshold levels, which the shape of the threshold CSF might not apply. Since the goal of the visual system is to represent the external visual world, it is important to characterize how changes in the level above
Threshold affect the everyday appearances of objects in scenes. This is where suprathreshold models of vision are needed.

![Graph](image)

**Figure 15. Suprathreshold contrast constancy (Georgeson, 1991).**

Figure 15 shows the results from a suprathreshold contrast matching experiment measured by Georgeson and Sullivan (1975). In this experiment, observers made apparent contrast matches between a standard 5 c/deg, a value near the peak of the CSF, grating and test gratings that varied from 0.25 to 25 c/deg. The uppermost suprathreshold function illustrates that all the gratings are set at contrasts close to their own contrast thresholds following the shape of the CSF at threshold. However, as the contrast of the gratings increase above threshold levels, the results shows that the apparent contrast match is obtained by adjusting the contrast of the test gratings to the same physical value as the contrast of the standard. At suprathreshold levels, the contrast matching function become increasingly flat across the whole spatial frequency range. This flattening of the equal-contrast contours is more rapid at higher spatial frequencies. The result suggests that two gratings of equal contrast but different spatial frequencies will produce different
retinal image contrasts, which implies that the visual system compensates at suprathreshold contrasts for the defocusing effects of the eye’s optics. This invariance of contrast perception phenomenon is known as contrast constancy. As an object moves away from an observer, its spatial-frequency content shifts to progressively higher values. Apparent contrast would decrease as viewing distance increased because contrast sensitivity decreases monotonically for higher frequencies. This apparent constancy confers a useful property on the perception of real objects. Providing the contrast that defines an object and its features is above threshold, perceived contrast of the object remains invariant across a wide range of distances.

Georgeson and Sullivan (1975) suggest that an active process is correcting rapidly for the neural and optical blurring seen at threshold for high spatial frequencies. They hypothesize that the multiple spatial frequency channels adjust their gain independently in order to achieve contrast constancy above threshold (compensate for earlier multiplicative attenuations that limit threshold sensitivity). Experimental evidence suggests that the visual cortex is the site at which this differential response to contrast occurs (Hess, Bradley, and Piotrowski, 1983). Further experiments demonstrated that these results are largely independent of mean luminance level and position on the retina (Georgeson, 1990; Kulikowski, 1976).
2.9. Summary

This chapter has reviewed some of the fundamental findings of psychophysical aspects of vision that need to be considered when developing a tone reproduction operator. The properties of early visual mechanisms determine both the limits and capabilities of visual perception that is important for advances in realistic image rendering. The cumulative achievement of adaptation indicates that the visual system is sensitive over a vast range of luminance level despite limits on the dynamic ranges of the individual neural units that make up the system. Moreover, the psychophysical experiments show that threshold visibility, color appearance, and visual acuity, and suprathreshold brightness, colorfulness, and apparent contrast are different at different illumination levels in scenes, and that these visual parameters change over the time-course of light and dark adaptation. All these findings should be considered when constructing perceptually based tone mapping operator. A more complete understanding of both early and higher levels of HVS is essential for advances in both the efficiency and the effectiveness of realistic image rendering, especially at suprathreshold level. By providing a brief summary of important characteristics of human vision, it is hoped that this chapter help understanding the interaction between HVS and tone mapping operator.
Chapter 3

A REVIEW OF TONE REPRODUCTION (MAPPING) OPERATORS

The goal of tone reproduction (mapping) is to produce realistic renderings of captured scenes, showing no more and no less visual content than would be visible if actually present to see the original scene, and to produce such rendering while facing the limitations presented by output devices (see Figure 16). As described in the previous chapter, the human visual system is capable of perceiving wide luminance values in the real world through a complex local adaptation process that allows regions of various luminance levels to be viewed effectively simultaneously. The problem is how to scale such wide luminance values to the limited displayable range of a standard output device. The pixel values in most output devices, such as CRTs and LCDs, are limited to a useful dynamic range of about two orders of magnitude represented by eight bits per pixel with values between 0 – 255, which falls far short of the range of real world luminance values. This is where tone reproduction operators come in to play their important role.

![Diagram](image)

Figure 16. Ideal tone reproduction process (Devlin, 2002)
Since the human visual system (HVS) is sensitive to relative luminance values, visualizing the high dynamic range (HDR) of world luminance value in a low dynamic range of output device is fundamentally possible. In order to create realistic rendering of a scene, tone reproduction should provide not only a method of compressing the range of luminance values that mathematically transform scene luminances into output device with limited capabilities, but also prediction of a various visual phenomena that mimics perceptual qualities such as contrast, brightness, and fine detail – all the visual sensations experienced by a human observer viewing the scene in the real world. In this regard, a more complete understanding of human visual system is needed for advances in realistic image rendering, especially at suprathreshold level. Although complete models of the visual system are still mysterious to a certain extent, enough information has been accumulated to develop tone reproduction operators to display HDR imagery.

The aim of this chapter is to provide brief overview of some of the tone reproduction operators that have been published to date. Reviews of tone reproduction operators can be also found in McNamara (2001) and Devlin et al. (2002). Tone reproduction operators can all be classified in two main categories: spatially uniform (global) and spatially varying (local).

Spatially uniform operators do not imitate local adaptation processes of the HVS but use an implicit normalizing factor in order to scale the scene luminance to fall within the limited range of display device. These operators handle the images as a whole and apply the same single constant transformation to every pixel discarding the original intensities of
the scene, which may cause perceptual differences. On the other hand, spatially varying operators mimic the local adaptation process in the retina by applying different scaling factors to different parts of an image. These operators reduce scene contrast locally, relative to neighborhood intensities, and convert the original intensities to the displayable intensities of the low-dynamic-range device. The following will only briefly examine the selected tone reproduction operators in terms of uniqueness and relevancy of the feature. The categorized tone reproduction operators are shown in Figure 17. The operators used for conducting this thesis are discussed in Chapter 4 and evaluated in Chapter 6.

<table>
<thead>
<tr>
<th>Spatially Uniform</th>
<th>Time independent</th>
<th>Time dependent</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Ward 1994</td>
<td>Ferwerda et al. 1996</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Spatially Varying</th>
<th>Time independent</th>
<th>Time dependent</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Schlick 1994</td>
<td>Fattal et al. 2002</td>
</tr>
<tr>
<td></td>
<td>Pattanaik et al. 1998</td>
<td>Reinhard et al. 2002</td>
</tr>
</tbody>
</table>

Figure 17. Categorization of Tone Reproduction Operators
3.1. Spatially Uniform Operators


Tumblin and Rushmeier were one of the first persons to bring attention to the tone reproduction problem and demonstrate how to construct a tone reproduction operator. The method is based on the suprathreshold brightness measurements made by Stevens and Stevens (1963) who proposed that power-law relation exists between luminance and perceived brightness. Steven's model of brightness and apparent contrast shown in Figure 18 indicates that as the luminance level increases, dark colors appear darker and light color appear lighter, resulting increase in the perceived contrast. The brightness of the surround increased as a power function of its luminance. This model of brightness perception is not valid for complex scenes but was chosen due to its mathematical convenience. The tone reproduction operator is defined by the response of two observer models and a display system model. Two observer models are a mathematical model of the visual system that includes all desired light-dependent visual effects while converting real-world luminance images to perceived brightness images. The display model converts display input values to viewed luminance values, including effects of ambient room light and performance of output device. The tone reproduction operator converts real world luminances to display input values, which are chosen to match closely the brightness of the real world image and the display image. The operator is limited to gray scale images only and notably lacking in spatial effects. The operator also fails for very dim images, displaying as anomalous middle gray images instead of black, and display contrasts for very bright images are unrealistically exaggerated.
Ward – A Contrast-based Scalefactor for Luminance Display (1994)

Ward’s method of contrast based scalefactor is based on perceived contrast sensitivity of visual system rather than brightness. The scaling factor is derived from the studies conducted by Blackwell (1946 & 1963). Blackwell performed a comprehensive investigation to determine the relationship between adaptation luminance, stimulus area, and threshold contrast and established a model of changes in visual performance due to the relationship between adaptation level and just noticeable difference (JND) in luminance (Blackwell, 1981).

Using a single linear scaling factor, Ward focused on preserving the visibility and perceived contrast in the scene while properly transforming real world luminance values to display luminance. The idea behind this operator is that JND in the real world should be mapped as a JND on the display device in order to preserve the visibility. One thing
that one needs to be aware of is that since Blackwell’s experiments were conducted in perfect laboratory conditions and the complexities of typical viewing conditions were not considered, the model used for building this operator is only an approximation of the human vision system. However, this simple linear scaling factor renders good results, and can be used for a wide range of applications where the lighting simulation is important, as it preserves the impression of contrast in the scene.


Ferwerda, et al.'s model is based on Ward’s (1994) method of matching just noticeable differences for a variety of adaptation levels between the world and display device to preserve contrast threshold visibility and considers changes in color appearance, visual acuity, and temporal sensitivity while preserving global visibility. The operator accounts for the transition between achromatic rod response and chromatic cone response by applying different tone reproduction operator depending on the level of adaptation and examining the aspect of adaptation over time. The operator is constructed by adapting the Ward’s model for cone t.v.i function to form a photopic operator and extending the model to include the rod t.v.i function to form a scotopic operator. The proper operator is applied depending on the adaptation level. For mesopic level of adaptation, both a photopic and a scotopic display luminance are combined appropriately. Similar to Ward’s method, the t.v.i function is obtained for both the real world and display luminance. Using a linear scale factor, the real world luminances are then transformed to photopic display luminances.
To simulate the loss in visual acuity, they used psychophysical data obtained by Shaler (1937), which describes the detectability of different spatial frequencies to changes in background luminance, to determine what spatial frequencies are visible. A Gaussian convolution filter is applied to remove any extraneous frequencies which are not discernible when adapted to the real world luminance in order to avoid ringing in the displayed image. Light and dark adaptation are also considered by adding a parametric constant to the display luminance, the value of which changes over time to mimic the time course of adaptation of visual system.


Ward Larson, et al. exploit the histogram equalization technique that incorporates the visual perception models to simulate visually accurate perception of real world luminance. The incorporated perception models are mainly influenced by earlier work done by Ferwerda, et al. (1996).

The operator utilizes the fact that 1) luminance levels occur in clusters, rather than constant across the dynamic range, 2) the human eye is sensitive to relative, rather than absolute, luminance values, and 3) the human eye rapidly adapts to a 1° visual field around the fixation point. To avoid halo artifacts and other forms of noticeable artifacts that can arise with a spatially varying multiplier, the operator adjusts the adaptation level based on the population of the luminance adaptation levels in the image. Cumulative distribution of the luminance histogram is used to identify clusters of luminance levels and initially map them to the display values.
The first step of the process is to calculate the brightness approximated as a logarithm of luminances averaged over 1° areas, deriving a global tone-mapping operator from locally averaged adaptation levels. A histogram and cumulative distribution function are then obtained from these reduced values. Using threshold sensitivity data from Ferwerda, et al. (1996), a histogram adjustment technique is applied to create an image with the dynamic range of the original scene compressed into the range available on the display device, subject to the contrast sensitivity limitations of the visual system. Although the operator utilizes a spatially uniform global mapping function, spatial variation is introduced by employing models of glare, chromatic sensitivity, and spatial acuity similar to those used by Ferwerda, et al. to increase perceptual fidelity.


Tumbling, et al. developed two tone reproduction methods for displaying high contrast images on a low dynamic range display by imitating some of the visual adaptation processes. The first method employs the psychophysical finding that HVS decomposes a scene into layers of intrinsic images each of which describes a perceived scene quantity, such as illumination, reflectance, and transparency (Gilchrist, 1994). This layer method separates the scene into intrinsic layers of illumination and surface properties. Three pairs of layers, diffuse, specular, and transparency reflectance and illuminant, are used to represent the scene. While preserving the reflectance layers, only the illumination layers are compressed by the sigmoid function adapted from the work of Schlick (1995) to reduce their contrast. As a consequence of compressing the only illuminant layers, the
contrast is reduced significantly but much of the detail is preserved. The compressed illuminant layers are then combined with the reflectance layers to form a reduced contrast display image. The limitation of this method is that it is practical only for synthetic (printed) images where all the layer information can be retrieved during the rendering process.

The second method is mainly influenced by eye movements and local adaptation characteristics of visual system that adjusts separately at different locations and luminances within a viewed scene. This method, known as the foveal method, assumes that the effects of local adaptation can be adequately recreated by viewing uniformly processed images created from foveally dominated measurements of the scene. The operator is constructed by revising the method of Tumblin and Rushmeier (1993), also building on the method of Ferwerda, et al. (1996) and Ward (1994). Considering a small circular region around the mouse cursor as the user’s “foveal neighborhood,” the operator interactively adjusts the displayed image to preserve local contrasts and the detail visibility in the fovea area while compressing the rest of the image. By clicking the mouse at the regions of interest, where viewer’s gaze, the foveal adaptation luminance value is computed by a precomputed image pyramid and the operator finds the desired display image luminances at each pixel. Then, finally, sigmoid compression function is applied to reassign pixel intensities to the displayable luminance values without truncating image highlights and details in the foveal region. Different from the layer method, this interactive foveal method can be used with any image and requires a computer display to convey the impression of high contrast.

Pattanaik, et al. developed an operator to create similar visual experiences caused by time-dependent adaptation from any desired input scene, static or dynamic, real or synthetic. The operator uses global rather than local adaptation model to rapidly create readily displayable color image sequences that may be robust enough for real-time use with interactive renderings. The operator is based on the perceptual models proposed by Tumblin and Rushmeier (1993) and extended to include an adaptation model, which transforms viewed scene intensities to represent retinal response for rod and cone, and appearance model, which expresses correlates of lightness and colorfulness. The forward version of these models computes viewed scene appearance, and the inverse version of these models computes display intensities that match the scene appearance.

The adaptation model is a simplified version of Hunt’s (1995) static model of color vision, amplified with exponential filters for time-dependent adaptation mechanisms to describe neural effects, pigment bleaching, regeneration, and saturation effects. These four components separately mimic the fast neural adaptation attributed to retinal interconnections and the much slower process of photopigment bleaching and regeneration in both rods and cones. The appearance model follows the concept used in Hunt’s model that reference white and reference black can be determined by the viewer and the appearance of any visual response can be judged against these standards. As suggested by Hunt, the reference white is determined as five times the current adaptation level and the reference black as 1/32 the intensity of the reference white. Assembling these models reproduces the appearance of scenes that evoke changes to visual adaptation.
The inverse models are applied to attempt to map scene appearance values to a display response values with as little distortion as possible.

3.2. Spatially varying operators

Chiu, et al. – Spatially Nonuniform Scaling Functions for High Contrast Images (1993)

Considering the fact that the HVS locally adapts to luminance and more sensitive to relative changes in luminance, Chiu, et al. believed that the tone reproduction should be performed locally rather than globally and introduced spatially varying scaling function that is essential for the display of high dynamic range image. The method is purely based on experimental results without incorporating adaptation issues or psychophysical models of HVS. The scaling function was designed by adopting the argument that the eye is more sensitive to reflectance than luminance. As a consequence of this, slow spatial variation in luminance is to some extent ignored by the eye, which implies that images with a wider dynamic range than the display device can be displayed without much noticeable difference if the scaling function has a low magnitude gradient. They tried several low pass filters, such as the Gaussian filter, the cone filter, and the Perlin filter, to create the images and found that the results were not affected by the type of filter. In other words, if the filter was wide, there was no apparent difference in the final result. By blurring the image to remove high frequencies, and inverting the result, the original details can be reproduced. However, a noticeable dark band or halo artifacts occurs at high contrast edge.
Schlick – Quantization Techniques for Visualization of High Dynamic Range Pictures (1994)

Schlick extended the idea of Chiu, et al. (1993) and Tumblin & Rushmeier (1993) and proposed more practical quantization techniques by improving computational efficiency and simplifying parameters. The operator was also developed purely based on experimental results and did not consider psychophysical models of the HVS. The operator utilizes a first degree rational polynomial function to map high dynamic range luminances to low dynamic range display devices in order to account for the non-linear response of both the display device (gamma correction) and visual perception. The function performed satisfactorily when applied uniformly to all pixels in an image. He then produced three spatially non-uniform mapping functions (low-pass filtering, micro-zones, segmentation) that mimic the local adaptation of visual system. The quantization driven by low-pass filtering was susceptible to unacceptable halo artifacts, which is common among spatially varying operators. The other two functions did not produce as satisfactory results as the uniform approach. Nevertheless, this work is worthy in its optimization of spatially varying techniques and suggesting some possible research directions.


Pattanaik, et al. applied more complete visual model of adaptation and spatial characteristics to develop a rather complicated tone reproduction operator that incorporates a multiscale representation of luminance, pattern, and color processing in human vision. They considered the problems of high dynamic range and perception of scenes at threshold and suprathreshold levels for realistic tone reproduction. The model
accounts for the changes in threshold visibility, visual acuity, and color discrimination, and suprathreshold brightness, colorfulness and apparent contrast that occur with changes in the level of illumination in scenes. This tone mapping function allows chromatic adaptation as well as luminance adaptation, but not the temporal aspects of visual processing model and, also, susceptible to halo effects as seen in other spatially varying operators.

The model consists of two main parts, the visual model and the display model. Prior to applying the visual model, the input image must be spatially sampled, which depends upon the Gaussian filters chosen for the image decomposition, to represent the visual system’s initial photoreceptor (three cones and rods) responses, and then, these three cones and a rod signals are calibrated to a luminance of 1.0 cd/m² for an equal-radiance spectrum. The vision model first performs the spatial decomposition process using the Laplacian pyramid and converts the images to adapted contrast signals using a luminance gain control. The adapted contrast cone images are transformed into opponent signals, and then, passed through contrast transducer functions. The transducer functions are used to model saturation of the visual neurons that signal contrast. Finally, the rod and cone signals are combined to produce signals that represent the three-dimensional color appearances of the input image. The display model then reverses these encoded appearance signals back through the model to recreate cone signals that reproduce the full color appearance of the displayable image on output device.
In addition to realistic tone reproduction capability, the introduced visual model can be applied to variety of other areas such as image quality metrics, image compression methods and perceptually-based image synthesis algorithms.


Funt, et al. presented two Matlab implementations of the main practical retinex algorithms to eliminate much of the variants from the original method. The retinex (originated from combining retina of eye and cortex of the brain) theory was first introduced by Land and McCann (1971) to compute the sensation of lightness. Since then many researchers have proposed several variants by improving computational efficiency and performance (McCann, et al., 1976 & 1999; Jobson, et al., 1997). The first implementation is a computer-based version described by McCann (1999), which creates a multi-resolution pyramid from the input by averaging image data. The second one is an older specialized-hardware version, which uses single pixel comparisons with variable separations. The main concept behind retinex computation of lightness at a given image pixel is the comparison of the pixel’s value to that of other neighboring pixels, which involves 4 steps of iterative operation: ratio, product, reset, and average.

Retinex takes the input image value as a logarithmic function of scene radiance with sufficient precision to generate equal lightness differences from equal radiance ratios. The log image is first averaged down to the lowest resolution level and computes lightness of each pixel by visiting each of its 8 immediately neighboring pixels and performing ratio-product-reset-average process for each visit to neighboring pixels. The
critical parameter of this operator is the number of iterations the neighbors are cycled through. The number of iterations controls the amount of dynamic range compression and sets the stage for a different level of post-processing by a LUT.

**Fattal, et al. — Gradient Domain High Dynamic Range Compression (2002)**

Fattal, et al.’s method was built on the fact that the HVS is more sensitive to difference in relative luminances, rather than absolute luminance, such that responds to local intensity ratio changes and reduces the effect of large global differences. However, they did not attempt to mimic the visual perception to create realistic rendering of a scene, but instead offer an effective, fast and easy-to-use form of tone reproduction.

The main concept of the operator is to attenuate the magnitudes of the large luminance gradients that exist in HDR scenes. Gradients of much smaller magnitude represent the fine details. The attenuation is progressive, penalizing larger gradients more heavily than smaller ones, thus compressing drastic luminance changes, while preserving fine details. The gradient attenuation function also employs a multi-resolution edge detection scheme constructed by a Gaussian pyramid to avoid halo artifacts. It is noted that although the computation of the gradient attenuation function is done in a multi-resolution fashion, ultimately only the gradients at the finest resolution are manipulated, thus avoiding halo artifacts that typically arise when different resolution levels are manipulated separately.

The operator first identifies large gradients at various scales, and reduces their magnitudes and a low dynamic range image is produced by solving a Poisson equation on
the attenuated gradient field. All the computations are done on the logarithm of the luminances to approximate the perceived brightness and to represent local contrasts in the luminance domain as gradients in the log domain. They claimed that the method does better job at preserving local contrast then some previous methods, has fewer visible artifacts than others, and yet is fast and easy to use.
Chapter 4

PROPOSED TONE MAPPING OPERATORS

Since the issues of realistic tone mapping were introduced, many operators have been proposed to overcome the problem of displaying HDR images. In order to simulate the realistic perception of world luminance levels on a standard output device, some operators utilize perceptual data based on psychophysical experiments, and others exploit a mathematical approach to simply compress the luminance range with aim of obtaining the maximum visibility on the display device and without considering the perceptual aspects of visual system. In any cases where tone reproduction attempts to simulate reality, one of the most important factors for rescaling the high dynamic range to fit into the smaller output dynamic range is that the final image maintains the lightness integrity of the original scene.

Nine methods primarily proposed for the display of HDR pictorial imagery were integrated and implemented for the display of non-pictorial imagery. The nine proposed operators were varied from simple linear scaling factor to more complete high end solution, which takes into account complex perceptual human attributes, in other words, from simple global (spatially uniform) mapping to complex multi-scale local (spatially varying) mapping to imitate the visual system. An inverse display characterization was applied at the end of each operator to account for inherent device nonlinearity before displaying. Controllable parameters for each operator were set as stated and
recommended in its reference, unless noted otherwise. The Matlab code used to implement each operator is shown in Appendix 11.1.

4.1. Linear Mapping

The most common approach is simply linear scaling to fit the high dynamic range image data to low dynamic range display device. Even though visual system certainly does not use a linear scaling function, it has been used widely for its strength of simplicity and speed. This linear method, rescaling the input digital value to 8-bit digital values, is initially used for encoding HDR images as a baseline operator. However, for pictorial images, linear scaling methods suffers from a known problem that it does not maintain visibility with high dynamic range, since very bright and very dim values are scaled to fall within the display’s limited dynamic range. It results in loss of image detail, local contrast, in bright areas and in dark areas. This approach reduces fine detail visibility, and distorts impressions of brightness and contrast. Thus, output images tend to appear light and often times contain a “milky” or “hazy” appearance in the shadow detail from a global reduction in the perceived lightness contrast and an increase in the mean lightness of the remapped image.

In order to overcome the limitations of the natural loss in perceived lightness contrast associated with linear lightness mapping, Braun and Fairchild (1999) have developed an adaptive lightness rescaling process that utilizes sigmoid mapping functions. By utilizing a sigmoid remapping function, both the highlight and the shadow detail are compressed to enhance the image contrast in the low dynamic range.

The idea of this gamut mapping technique is adapted for displaying HDR imagery. The hypothesis of using sigmoid functions for lightness remapping is based on the phenomenon of simultaneous lightness contrast. It is possible to make the dark colors in an image look darker by making the light colors lighter. The form of the sigmoid functions was derived from a discrete cumulative normal function (S), given in Equation 1, where \( x_0 \) and \( \sigma \) are the mean and variance of the normal distribution respectively, \( i = 0, 1, 2\ldots m \), and \( m \) is the maximum digital value used in the image data.

\[
S_i = \sum_{n=0}^{n=i} \frac{1}{\sqrt{2\pi} \sigma} e^{-\frac{(x_n-x_0)^2}{2\sigma^2}}
\]

Equation 1

The \( x_0 \) and \( \sigma \) parameters control the shape of the sigmoid. The value of \( x_0 \) controls the centering of the sigmoid and \( \sigma \) controls the slope. Decreasing \( x_0 \) has the effect of applying more highlight compression, while increasing \( x_0 \) results in more shadow compression. Decreasing the \( \sigma \) value has the effect of increasing the contrast of the remapped image giving the appearance of a larger dynamic range. By adjusting \( x_0 \) and \( \sigma \) it is possible to
tailor a remapping function with an appropriate amount of image contrast enhancement and highlight and shadow lightness compression.

The tone mapping function involves a simple interpolation process. The parameter $x_0$ and the $\sigma$ can be estimated using a sequential linear interpolation process to construct optimum sigmoid function. $x_n$ is normalized input digital value of the image ranging from 0 to 100, representing CIE L* value. The 75 percent point of the cumulative histogram of the input image is then determined. The value is compared to the 75 percent points of the reference lightness obtained from the psychophysical experiment performed by Braun and Fairchild (1999) to optimally set the parameter $x_0$. The reference lightness parameters have three category; high, medium, and low lightness-classes. The parameter $x_0$ is estimated by interpolating the reference parameters with the 75 percent points of the cumulative lightness histogram for the input image. The parameter $\sigma$ is also estimated in the same way. Once the optimum sigmoid function is acquired, the input digital values are then transformed by the function to obtain properly rescaled displayable image.

4.3. Localized Sigmoid Mapping

Localized sigmoid mapping is applied to locally control the contrast of the HDR image. By locally applying sigmoid mapping, it is hypothesized that more information can be conveyed because local perceptual contrast in a wider range of the scene will be preserved. A sigmoid look-up table was created for every pixel in the input image by locally setting the parameter $x_0$. Gaussian blur in the frequency domain (creating a low-pass version of the image) was utilized to set the $x_0$ to perform this localized adaptation.
Equation 2 shows the Gaussian filter used for acquiring the low-pass version of the image. The degree of adaptation depends on the amount of blurring, which is controlled by the width of the filter (\( \sigma \)). \( \sigma \) was set to 3 to reduce the problem of haloing where contrast of the local neighborhood was significantly high. The parameter \( \sigma \) for sigmoid function (Equation 1) was set by the mean of the input image value. The parameter \( x_n \) contained the same range as the input digital values. Due to the fact that it is a local operator that the process has to be performed in pixel-by-pixel base using independent sigmoid look-up table for each pixel, high computational cost is one of the critical drawback of this operator. Moreover, as it is a common artifact for other spatially varying operators, this method also suffers strong halo artifacts. Some artifacts were retained in the final results.

\[
GF = e^{-\left(\frac{\sqrt{x^2+y^2}}{\sigma}\right)^2}
\]

\[
LowIMG = FFT^{-1}(FFT(img)FFT(GF)) = x_0 \quad \text{Equation 2}
\]


Previous work performed by Montag (1999) has suggested that using the scale based on the CIELAB uniform color space with an added hue and chroma component led to significantly better performance among the five different perceptual scales tested for encoding univariate digital elevation maps (DEMs) by extending the path length of the univariate scale by adding color to the path. The study was done in order to evaluate how different encoding schemes affect visualization of what is invisible or unavailable to the
human visual system. Montag’s method was conducted in this study to compare this visualization technique to the HDR operators.

The operator was formulated by first creating look-up table (LUT) for L*, C*, and H*. L* LUT was obtained by normalizing input digital value into 0 to 100 linearly and H* LUT was also linearly spaced from 180 to 630 by the maximum input image digital value, so that, there were one to one relationship between LUTs and input digital value. C* LUT was constructed using the following equation, \(148 \times \left((L^* \text{ LUT}/100) - (L^* \text{ LUT}/100)^2\right)\). Once all the LUTs were generated, corresponding L*, C*, and H* values were assigned for each digital value of the input image. Assigned LCH values were then converted to Lab values. Using the white point of the display, which is \(X = 117.6\), \(Y = 131.8\), and \(Z = 141.0\), the Lab values were transformed to XYZ tristimulus value. Finally, inverse display characteristics were applied before displaying final result.

4.5. PhotoShop (Auto-levels)

As part of one of the most popular graphic software application with the capability of handling 16bit image, the performance of the Photoshop tool called “auto-levels” was evaluated with the other operators. Images were opened as raw data, and then auto-levels was performed to adjust the image contrast. Auto-levels automatically corrects the tonal range of an image by defining the lightest and darkest pixels in the image, and then redistributes intermediate pixel values proportionately (Adobe Photoshop, 2002). This allows the enhancement of the contrast of an image.

Local color correction operation by Moroney (2000) is based on non-linear masking providing a simple, computationally efficient way to locally adjust the contrast of image. The process basically performs a pixel-by-pixel gamma correction by utilizing an inverted low-pass filtered version of an input image. One thing that it has to be noted is that this method is not based on any visual perception model.

The idea of this local color correction method is conducted for use of displaying high dynamic range image. In order to use the method effectively, it was first assumed that the input HDR digits are proportional to the logarithm of the image. The image was simply compressed by log before processing through the operator. The operator consists of two parts: 1) creating the mask image, 2) the combination of the mask and the input image. The low-pass filtered mask image is obtained by Gaussian blur shown in Equation 2 with \( \sigma \) set to 15. This low-pass image is then inverted to be served as a mask in the process. The combination operation is then a variable power function where the exponent is computed from the mask as shown in Equation 3. When the pixel-by-pixel gamma correction process is done, log scaled values are inverted by exponential function to obtain final result.

\[
Output = \left( \frac{Input}{Max_{input}} \right)^{2 \left( \frac{Mean_{mask} - Mask}{Mean_{mask}} \right)}
\]  
Equation 3

iCAM includes spatially localized adaptation and spatially localized contrast control that can be applied to the problem of displaying high dynamic range image (Fairchild and Johnson, 2004 & 2002). iCAM was originally designed for truthful rendition of overall color appearance with spatial vision attributes. However, as it is described by Johnson and Fairchild (2003), the iCAM framework can be tuned for the prediction of the appearance of high dynamic range images, which is one of the most interesting applications of iCAM.

iCAM has a problem of producing the pinkish cast over the image resulted from the improper input range of the images. The problem can be corrected by scaling the input range of the image and using device characterization for transforming the input digital value to XYZ device independent coordinates. The scaling factor, shown in Equation 4, is estimated by dividing 25 by 99 percentile of the normalized input digital value. Then, the digital values are multiplied by the scaling factor. Figure 19 illustrates the flow chart of iCAM for rendering HDR images.

\[
\begin{align*}
    Norm_{input} &= \frac{Input}{Max_{input}} \\
    Scale &= \frac{25}{99\% \text{ value of } Norm_{input}} \\
    IM_{in} &= Norm_{input} \times Scale
\end{align*}
\]

Equation 4
Since iCAM requires colorimetrically characterized data of the image as an input, the scaled image needs to be specified in terms of relative CIE XYZ tristimulus values using device characterization. The first step of rendering process is to account for chromatic adaptation. The chromatic adaptation transformation is linear von Kries transformation with an incomplete adaptation factor, which is identical to that of CIECAM02 (Moroney et al., 2002). The adaptation field is derived from a low-pass version of the image itself as the adapting whitepoint to perform a localized adaptation, utilizing Gaussian blur in the frequency domain at each pixel location. Prior to perform the chromatic adaptation, a global whitepoint shift toward a uniform illuminant D65 field is required to correlate with
the IPT color space because iCAM is implemented using IPT color space (Ebner and Fairchild, 1998), which is only defined for D65.

Once the chromatic adaptation is performed, the XYZ values are then transformed to IPT opponent color space by first converting the XYZ values into LMS cone responses that are necessary for constructing a uniform perceptual color space and correlates of various appearance attributes. The cone responses are then compressed using a nonlinear power function, which is a critical aspect of the iCAM model. This nonlinear power function is a series of local tone reproduction curves that are modulated on a per-pixel-basis according to the localized luminance and surround to predict the Hunt, Stevens, and Bartleson and Breneman effects and also enable tone mapping of HDR images into low dynamic range display systems in a visually meaningful way. Another low-passed version of the image is used to calculate this series of power functions. This spatially varying local tone mapping is inspired by the local contrast adjustments introduced by Moroney (2000). The modulated cone responses are linearly transformed into the IPT opponent space, which is the last step of the forward model segment of the iCAM.

To properly display the image on an output device, the appropriate inverse model should be applied. The display viewing conditions set the parameters for the inversion of the IPT model and the chromatic adaptation transform. No clipping was performed at the final stage in order to prevent loss of any information that might be critical.

The Fast Bilateral Filtering introduced by Durand and Dorsey (2002) is based on a two-scale decomposition of the image into a base layer (encoding large-scale variations) and a detail layer – an approach which builds on Tumblin and Turk’s (1999) LCIS method and Tumblin et al.’s (1999) layering method. The method has the capability of taking a high dynamic range image as input and compresses the contrast of the base layer by bilateral filtering while preserving the details of the original image. The detail layer is the division of the input intensity by the base layer. Bilateral filtering is a non-linear filter introduced by Tomasi and Manduchi (1998) shown in Equation 5, where \( k(s) \) is a normalization term, \( f \) is a spatial kernel, and \( g \) is an edge-stopping function in the intensity domain. The function derives from Gaussian blur, but it prevents blurring across edges by decreasing the weight of pixels when the intensity difference is too large. All the computation is done in the log of pixel intensities. Prior to displaying the result, the log scale has to be inverted by exponential function. Parameters are set as it is described in Durand and Dorsey (2002). As with other recent tone reproduction operators, perceptual accuracy is not considered and the operator does not attempt to model human vision.

\[
J = \frac{1}{k(s)} \sum f(p - s) g(I_p - I_s) I_p
\]

\[
k(s) = \sum f(p - s) g(I_p - I_s)
\]

Equation 5
4.9. Reinhard et al. (2002) – Zone System

The Zone System proposed by Reinhard et al. (2002) utilizes the automatic dodging-and-burning technique used in traditional photography to accomplish dynamic range compression. To improve the overall visibility, the operator firstly applies a scaling to the entire image to reduce the dynamic range and then modifies locally the contrast of some regions by highlighting or darkening. The operator employs spatially varying tone mapping function, which enables contrast to be controlled locally in the image over regions bounded by large contrasts. The operator is again focused on visibility rather than perceptual accuracy.

The method exploits the center-surround function derived from Blommaert’s model (Blommaert and Martens, 1990) to estimate the size of a local region by measuring local contrast. The function consists of a circularly symmetric Gaussian function, which operates at different scales \( s \) at different image positions \( (x, y) \), and convolves with image in spatial domain as shown in Equation 6. The defined center-surround function is also shown in Equation 7, where \( V_1 \) is center and \( V_2 \) is surround responses from Equation 6. The center-surround ratio is set to 1.6 as recommended. The free parameters \( a \) and \( \varphi \) in Equation 7 are the key value set to 0.18 for normal-key and a sharpening parameter set to 8.0 respectively.

\[
R_i(x, y, s) = \frac{1}{\pi (\alpha_i s)^2} \exp \left( -\frac{x^2 + y^2}{(\alpha_i s)^2} \right)
\]

\[
V_i(x, y, s) = L(x, y) \otimes R_i(x, y, s)
\]

Equation 6

Equation 7
\[ V(x, y, s) = \frac{V_1(x, y, s) - V_2(x, y, s)}{2^a \frac{d}{s^2} + V_1(x, y, s)} \tag{Equation 7} \]

The local area can be defined by the largest area around a given pixel with no large contrast changes. Since \( V_1(x, y, s) \) and \( V_2(x, y, s) \) provides a local average of the luminance around \((x, y)\) at the same scale but a different size, \( V_1 \) and \( V_2 \) will be different in high contrast areas. In order to find the first appropriate scale, the center-surround function is evaluated at different scales (8 discrete scales increasing by factor of 1.6) and the threshold is set to 0.05 for \( V \). Once the scale is selected, \( V_1(x, y, s_m) \) becomes a local average for that pixel. The local tone reproduction operator can then be formulated as shown in Equation 8. All the parameters are set as recommended.

\[ L_d(x, y) = \frac{L(x, y)}{1 + V_1(x, y, s_m(x, y))} \tag{Equation 8} \]
Chapter 5

NON-PICTORIAL (SCIENTIFIC) IMAGERY

The term, non-pictorial, refers to scientific imagery captured outside the visible wavelength region or of objects not accessible to the human eye, such as hyperspectral data captured by spacecraft or aircraft, astronomical images captured using non-visible wavelengths, or characteristics of human tissue obtained in medical imaging. In principle, any data arranged in a two dimensional matrix which can be displayed as an image can be considered.

Five different sources of scientific imagery were utilized in this study, and one pictorial image was also included for comparison. They are briefly described in Table 1 and histograms and thumbnails of the images are shown in Figure 20. The processed radar image was cropped to 930(rows) x 800(columns) in order to display the image in true size. All the rendered images are shown in Appendix 11.2.

<table>
<thead>
<tr>
<th>Image Type</th>
<th>Source</th>
<th>Max digit</th>
<th>Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>Astronomical</td>
<td>Hubble Space Telescope</td>
<td>65455</td>
<td>1000x650</td>
</tr>
<tr>
<td>Medical</td>
<td>Magnetic Resonance</td>
<td>1655</td>
<td>256x256</td>
</tr>
<tr>
<td>Hyperspectral</td>
<td>AVIRIS (Airborne Visible InfraRed Imaging Spectrometer)</td>
<td>28175</td>
<td>614x512</td>
</tr>
<tr>
<td>Radar</td>
<td>AIRSAR (Airborne Synthetic Aperture Radar)</td>
<td>16384</td>
<td>1485x2161</td>
</tr>
<tr>
<td>Infrared</td>
<td>WASP (Wildfire Airborne Sensor Program)</td>
<td>2302</td>
<td>640x510</td>
</tr>
<tr>
<td>Pictorial</td>
<td><a href="http://www.debevec.org">http://www.debevec.org</a> (Memorial Church)</td>
<td>65536</td>
<td>768x512</td>
</tr>
</tbody>
</table>

Table 1. Information of the imagery exploited in the study
The astronomical image is a 16 bit binary image captured by the Hubble Space Telescope, which is an image of dying star. The image holds a peak pixel values at around 200 ADU, but there is real information at the level of 0.03 ADU. The medical image is a magnetic resonance image of a human spine that contains about 11 bits of amplitude resolution. The hyperspectral image is a 910 nanometer (nm) portion of multispectral imagery of Rochester, New York area (specifically, around RIT campus) captured by AVIRIS (Airborne Visible InfraRed Imaging Spectrometer). This image delivers near 15 bits of information about the surface and atmosphere based on molecular absorption and particle scattering signatures. The radar image is a scene of Nabesca, Alaska captured by AIRSAR (Airborne Synthetic Aperture Radar), designed and built by the Jet Propulsion Laboratory (JPL) NASA, which contains 14 bits of data collected by penetrating through clouds at night. The infrared image is 11 bit imagery from long-wave band of the electromagnetic spectrum taken by WASP (Wildfire Airborne Sensor Program). The pictorial image is a 16 bit Memorial Church image from http://www.debevec.org.
Figure 20. Histograms and thumbnails (iCAM processed) of the imagery exploited in the study
Chapter 6

**Psychophysical Experiments**

The psychophysical experiments were conducted on a 23” Apple Cinema HD flat-panel LCD display connected with an Apple Power Mac G4 dual 1GHz processor. A MATLAB program was used for creating and running the experimental GUI. The display device was characterized using a LMT C1210 Colorimeter and the method described in Day et al. (2004). The measured chromaticity of display white point was $x = 0.30$ and $y = 0.34$ and the luminance was 179 cd/m$^2$.

Since this project deals with non-pictorial imagery, the fidelity of the processed images cannot be judged by comparison with the original scene. Instead, three psychophysical experiments were carried out to measure the effect of the different operators on the perception of the various images. Figure 21 shows the Medical image rendered with nine different operators (see Appendix 11.2 for other imagery).
Figure 21. The Medical image rendered with nine different operators
6.1. Two Paired-Comparison Experiments

Two paired-comparison experiments were conducted to judge both the observers’ preference and the judged scientific usefulness of the images. The goal of the first experiment was to determine which encoding schemes rendered the high dynamic range images in more preferable way. In this task, observers were instructed to choose the image that they preferred in each pair. In the second experiment, the same stimuli were used but the observers were instructed to choose the image in each pair that they considered to be “more scientifically useful.” Observers were allowed to use their own criteria for making these judgments.

Twenty-five observers participated in the experiment. The six images shown in Figure 20 were processed through the nine operators discussed in Chapter 4, producing 36 possible pairs for each image and 216 pairs for each experiment. These images were then randomly displayed side by side. The preference task performed first, and then usefulness of images was judged at once, which, on average, took 40 minutes to complete both experiments.

To further elucidate the success of HDR rendering, the experiment was extended for observers with expertise for a particular image type. Twenty-one radiologists participated in evaluating the success of rendering HDR Medical image. Since the experiment was performed on the web for convenience and easy participation, the Medical image was processed by nine different operators adjusted for typical output device characteristics (e.g. sRGB and gamma of 2.2) and again evaluated in paired-comparison paradigm.
Every possible pair of processed images (total of 36 pairs) was presented and the expert opinions from radiologists were collected by asking to choose which image from each pair would be a more useful image based on their expertise.

6.2. Target detection Experiment

A third psychophysical experiment was performed to measure how the change in contrast tone mapping due to the various operators affected the detection of a target as measured by the amplitude of the target in the raw image data. This experiment used a two-alternative forced-choice method of constant stimuli paradigm to find the threshold for detecting embedded noise in the Medical image. The task of target detection can be considered as a way of determining the change in detectability of a “tumor” embedded in the image.

Thresholds, in terms of the original digital values in the image data, were measures for three different targets in the image as shown in Figure 22. Each of the targets had a different spatial size and location in the image. The targets consisted of normally distributed random noise in a Gaussian envelope. For each target, a series of images were precomputed with different amplitudes of noise added to the original image data. These images were, in turn, processed through the nine operators above. The targets were placed at the three different lightness areas, dark-, mid-, and high-tone areas separately, and the images were process with each operator. Then these images were displayed side by side with an image processed with the corresponding operator without the target, creating 189 possible pairs. Each target image was presented randomly with the
corresponding rendered operator without the target 60 times. The experiment was divided into several sessions to complete the task. The observer’s task was to choose which image had the target. When the target amplitude was not detected, the observer would have a 50% chance of correctly guessing the image that contained the target. This within-subject design was analyzed using Probit analysis for each subject participated in the experiment to determine the corrected-for-chance 50% threshold for target detection. Two subjects participated in the experiment. A comparison of these two subjects was performed.

Figure 22. Illustration of three different targets; images were rendered by the Bilateral filtering method; an original processed image (upper left), smallest target in high tone area (upper right), medium target in middle tone area (lower right), and largest target in dark tone area (lower left).
CHAPTER 7

RESULTS AND DISCUSSION

7.1. The Paired-Comparison Experiments

7.1.1. Paired-comparison analysis

The paired-comparison data was converted to interval scales for analysis by employing the Thurstone’s Law of Comparative Judgments (Case V) (Engeldrum, 2000). For the preference task, observers were asked to choose which of the two images they preferred in terms of overall image quality. For scientific usefulness, no specific criteria were given to observers. They had to decide what is meant by “scientifically useful,” which may have introduced some difficulty in deciding what criteria to use. The image preference and judged scientific usefulness of all images are shown in Figure 23 (separate plot for each imagery type is shown Appendix 11.3). The error bars on all plots were calculated in terms of interval scale units for a 95% confidence interval (Montag, 2004). Both figures indicate that performance of each operator depends on the image type. Comparison of these graphs also shows the different pattern of response between the two tasks. This distinction is more apparent in average performance data shown in Figure 24. The low correlation between the two sets of results demonstrates that the observers were using different criteria for the two tasks. As shown in Figure 25, the data has an R-squared value of 0.305. This value clarifies that there are substantial changes in interpreting the data in the image when judging the scientifically usefulness. However, the images processed using the Zone System was judged high both in preference and
scientific usefulness compared to the other operators. The Local Sigmoid function showed the most prominent changes between the two tasks. Observers did not prefer the images processed by the Local Sigmoid method but they found that it revealed data that were judged to be more scientifically useful.

Figure 23. Results of paired-comparison data for all images
Figure 24. Average performance of paired-comparison experiments; Preference (upper), Scientific usefulness (lower).

Figure 25. Plot of Preference vs. Scientifically Useful; shows correlation between two data.
Individual variability for all the imagery is plotted using diagrams that show the observer’s response patterns in Figure 26 (see Appendix 11.4 for all other figures). Individual observer data is shown along the rows and the columns represent the operator types. A box with a lighter shade indicates that the operator in that column was chosen more frequently in the experiment than the other operators. Therefore, white boxes show often chosen operator types and black boxes show rarely chosen types. The apparent stripe pattern is the indication of consistent responses among the observers. For the Astronomical image, Figure 26, left, illustrates that observers agreed on their preference judgments but not on their judgments of scientific usefulness. By contrast, Figure 26, right, shows similar individual agreement on both preference and scientific usefulness task for the Pictorial image. The results depend largely on image type.

![Figure 26. Schematic diagram for Astronomical and Pictorial image: Preference(Left), Scientifically useful(Right).](image)
The Medical image was further analyzed by comparing the paired comparison experiment performed by Radiologists with the results of Non-radiologists to elucidate if they have similar opinions on the success of rendering the image. Figure 27 illustrates the comparison between the results of Radiologists (expert) and Non-radiologists (Naïve, scientific usefulness experiment). This comparison indicates the similar trends in opinion between the two groups; the best three operators are the Zone System, Bilateral Filtering, and Local Sigmoid and the worst two operators are the Spiral and Linear methods. However, the results of radiologists, Figure 27 (left), show greater distinction in performance and that the images rendered by the operators with localized adaptation feature are apparently more useful than the one reproduced by the operators with global mapping. The diagrams shown in Figure 28 indicate that two diagrams share similar striped patterns. However, the results of Radiologists, Figure 28 (left), show a more apparent striped pattern showing consistent response among the experts. Dark vertical lines in these diagrams imply that the Spiral and Linear methods are chosen by the both groups to have lower performance.

Figure 27. Radiologist (left) vs. Naïve (non-radiologist’s scientific usefulness data, right)
The Zone System performed well for the majority of the tested image. Nevertheless, it did not achieve the same result for the Infrared image. As is illustrated in Figure 29, performance of operators can be divided into two groups. Except for iCAM, operators with local contrast feature behave worse than the ones without so that simple linear mapping renders the image better. Figure 30 shows the plot of the Infrared image's pixel by pixel values for the linear rendering versus the Zone System (left) and versus iCAM (right). The Linear vs. Zone System and Linear vs. iCAM plots show how the operator with spatial filtering rendered the image compared to one without. For this particular image, the relationship between Linear and Zone System can be explained by a simple gamma curve. The shadow and highlight areas are more compressed in the image.
processed by Linear method than Zone System. However, comparing to iCAM, only the shadow regions are more compressed and other regions are linearly related. These results are different depending on the spatial structure of the image.

![Figure 29: Plot of paired-comparison result for InfraRed image: Blue dot (*) represents Preference results and Red asterisk (*) for Scientific usefulness](image)

![Figure 30: Comparing processed InfraRed image; Linear vs. Zone system and Linear vs. iCAM.](image)

PhotoShop shows the worst performance for pictorial image (Figure 31), though it performs well on average (Figure 24). This result might be explained by the histogram of the image. The histogram of the image, see Figure 20, shows that the majority of pixels are located at extremely low ends and only small amount of pixels are dispersed over the complete range. Photoshop tends to produce better results with images that have a wider
distribution of pixel values, such as the Radar image. A simple method for rendering HDR pictorial imagery is to apply a 99 percentile clipping and a gamma correction. These techniques are simple but powerful enough to obtain acceptable reproduction.

The Spiral encoding is the only operator that adds color to the image. This operator can be treated as a linear L* mapping since the digital values were first mapped linearly to L* values, and then, chroma and hue values were add to the monochrome image. Observers tend to favor color over monochrome image when tone mapping is acceptable. However, this tendency diminishes when judging the scientific usefulness, see Figure 24. Due to the limitation of tone mapping, spiral encoding can’t reveal much hidden information. If other tone mapping techniques can be combined with color, the performance might show a possible increase.

The Local Color Correction operator is the worst method to use for rendering the HDR images on average and especially for the Radar and InfraRed image. However, this
method performed well for the Pictorial and Astronomical image. It is better than operators with global mapping but not good enough to compare with operators with local contrast mapping function. The performance of iCAM is neither excellent nor bad. The results are somewhat expected since iCAM is intended to render a pictorial scene truthfully rather than enhancing it. The aim of iCAM is accurate prediction of a variety color appearance phenomena that mimic the human perception. Experiments on accuracy, which is not possible for scientific imagery, can be conducted to support this hypothesis by employing pictorial imagery.

7.1.2. Goodness-of-fit test

A goodness-of-fit test was performed to evaluate the assumptions used in Thurstone’s Law such as the normality in the observed distribution of response (Engeldrum, 2000). Mosteller’s Chi-Square Test was employed to see whether the data came from a normal distribution. In order to validate the assumptions and appropriateness for use of Thurstone’s Law, the Chi-Square value from the Mosteller’s Test should be less than the critical value to demonstrate that the data come from a normal distribution. If this condition is met, Thurstone’s Law is a good fit for the data.

The tests results are shown in Table 2, which indicates that most of the experiment data fail the goodness-of-fit tests. The chi-square values are much higher than the critical value, except the Medical and Hyperspectral images for preference experiment. This could mean that the paired-comparison analysis is not valid since it doesn’t meet the assumptions of Thurstone’s Law. This may be due to substantial number of unanimous
judgments by the observers or observers may have judged the images based on more than one dimension using different criteria. Further analysis was needed to find the possible reasons. A dual scaling analysis (Nishisato, 1994) was performed to find hidden structure within a data set.

<table>
<thead>
<tr>
<th>Image</th>
<th>Preference</th>
<th>Scientifically Useful</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Chi-Value</td>
<td>Critical Value</td>
</tr>
<tr>
<td>Medical</td>
<td>37.54</td>
<td>41.34</td>
</tr>
<tr>
<td>Hyperspectral</td>
<td>38.30</td>
<td>41.34</td>
</tr>
<tr>
<td>Astronomical</td>
<td>257.44</td>
<td>41.34</td>
</tr>
<tr>
<td>Radar</td>
<td>64.38</td>
<td>41.34</td>
</tr>
<tr>
<td>InfraRed</td>
<td>159.08</td>
<td>41.34</td>
</tr>
<tr>
<td>Pictorial</td>
<td>60.84</td>
<td>41.34</td>
</tr>
</tbody>
</table>

![Table 2. Goodness-of-fit test for paired-comparison experiments](bitmap)

7.1.3. Dual Scaling Analysis

Dual scaling is a technique that can be used to investigate the hidden structure within a categorical data set through complex mathematical manipulations. This technique can be thought as eigenvector analysis or principal component analysis proving multidimensional decomposition of data. The data are sorted into dimensions to look at the most informative portion of data that hold the most amount of variance, then the second most informative data, and so on, to explain the data.

Figure 32 shows the results of the dual scaling analysis for the preference data explained by first two dimensions. The red stars and the green circles represent the configurations of algorithms and observers, respectively, in the first two dimensions. The plots may be
interpreted by the relative proximity of the algorithms and observers on the plot rather than the actual values on the axes. The critical thing is the geometric relationship between the algorithms and observers relative to one another. The dual scaling plots for the preference data show similar results to the paired comparison results in the first dimension. The algorithms with similar performance are close in relationship to one another and overlapping observer configurations show that most of the observers are relatively close to the operators with better performance.

In addition, observers with similar responses are aligned along the first dimension in the configurations. A spread in the observer configurations in the first dimension indicates individual variability in the patterns of response.
Figure 32. The dual scaling results for the preference experiment.
Figure 33. The variance plots for dual scaling results for the preference experiment.
For example, in the plot of the Hyperspectral image (Figure 32), the Photoshop and Zone System methods, which are the top two operators chosen by the observers’ preference, are located close to each other and the majority of observer configurations are placed relatively close to these operators. However, for the Medical image, there is no grouping of the observer data that fall mainly in one dimension or the other. The observer configurations are spread over the plot suggesting multidimensionality of the data and questioning the validity of the paired comparison analysis.

The variance plots are shown in Figure 33 that corresponds to the dual scaling analysis shown in Figure 32. The individual dimensions and the cumulative variances are explained in these plots. The plots illustrate that, except for the Medical image, the variances in the first dimension are much larger than those of the second dimensions. We can infer from these plots that the data can be explained mainly by one dimension. Although the validity of the paired comparison analysis is questioned by the results of the goodness-of-fit test, it is still possible that the data may be unidimensional and Thurstone’s Law is applicable to the data set. However, the plot of the Medical image shows that most of the variance is not accounted for in the first dimension. This result corresponds to the dual scaling plot shown in Figure 32 and supports the evidence that the data may be multidimensional.
Figure 34. Dual scaling results for the scientific usefulness experiment.
Figure 35. The variance plots for dual scaling results for the scientific usefulness experiment.
The dual scaling analysis for the scientific usefulness data are shown in Figure 34 representing first two dimensions. The results mimic the corresponding paired comparison analysis and also similar to the dual scaling results of preference data. The observer data falls close to a single dimension and operators with similar performance are located closer to one another. However, different from the dual scaling of preference data, the observer data of the Medical image are more closely related along a single dimension representing possible unidimensionality, furthermore, the observer data of the Astronomical image are more widely spread over the plot suggesting multidimensionality of the data. These results are also evident in the variance plots shown in Figure 35.

Figure 35 shows that most of the variance is in the first dimension for all images but the Astronomical image. The plot of Astronomical image shows that the variance in the first dimension is not much larger than the second dimensions. Since the majority of the data cannot be explained by the first dimension, there is further evidence that the data may be multidimensional. However, the data for all other images is mainly unidimensional. Although the results of the paired comparison analysis is once doubted by the goodness-of-fit test, the dual scaling analysis and variance plots provides the evidence that Thurstone’s Law is valid for this data set. For both preference and scientific usefulness data, the interval scale from the paired comparison analysis may be accurate and applicable.

The Radiologists’ data was also evaluated using the dual scaling analysis. The Figure 36 illustrates the first two dimension of the dual scaling analysis on the Figure left and the
corresponding variance for the individual dimension and the cumulative variances on the Figure right. The configuration of the plot is similar to the previous dual scaling plots. The observer data is placed closer to a single dimension. The most of the data can be explained by the first dimension as shown in the variance plot. Therefore, the paired comparison analysis may also be valid for the Radiologists’ data.

![Figure 36. The dual scaling result and the corresponding variance plot of the Radiologists’ data.](image)

The Radiologists’ data and the Non-radiologists’ data was combined to perform the dual scaling analysis in order to examine whether there is a categorical difference depending on their experience. Figure 37 shows the dual scaling results for the combined data of the Radiologists and Non-radiologists. The dual scaling result is shown on the left; the green circles represent the Radiologists’ data, the red circles symbolize the Non-radiologists’ data. Although the Non-radiologists data is rather spread within the first two dimensions, there is no clear distinction in opinions between the Radiologists and the Non-radiologists. All the observer data is closely related to each other along a single dimension suggesting the possibility that the data may be unidimensional. The corresponding variance plot shown in Figure 37 right illustrates the similar evidence. The variances in the first
dimension are much larger than those of the other dimensions, which imply that most of the data can be explained by the first dimension. Although the Non-radiologists’ data is somewhat spread over the plot, the data can be considered as a unidimensional and there is no significant difference between the Radiologists’ and the Non-radiologists’ opinion. They tend to use similar criteria regardless of their experience and expertise when judging the usefulness of rendered images.

Figure 37. The dual scaling result and the corresponding variance plot for the data combing Radiologists’ data and Non-radiologists’ data. (Green circle: expert, Red circle: naive)
7.2. Target Detection Analysis

A target detection experiment was conducted to measure the detectability of an embedded noise target in the Medical image to demonstrate the effect of the algorithms on target detection. It is obvious that the spatial structure and tone scale mapping of the images and their resultant renderings will introduce distortions that will effect target detection. Therefore, the characteristics of targets in the image should be taken into account when determining the appropriate rendering algorithm. In theory, better algorithms will allow detection of targets with low amplitude regardless of the surrounding local contrast.

The noise-tumors were first obtained by creating normally distributed random noise and then multiplying this with a Gaussian envelope to reduce the sharp onset of the noise. The size of the Gaussian filter was set to 5, 8, and 10 pixels on 15x15, 20x20, and 30x30 noise patch for high-, mid-, and dark-tone regions respectively. The amplitude of noise was varied depending on the image type and was optimally set in seven steps. Two subjects participated in the experiment and each stimulus was repeated 60 times for each person. The results were analyzed using Probit analysis for each subject participated in the experiment to determine the corrected-for-chance 50% threshold for target detection. Figure 38 shows the plot of Probit analysis with 95% Fiducial limits (see Appendix 11.5 for complete list of plots). The results of two subject data are similar to one another. Some of the plots shows larger Fiducial limits than the others indicating low level of precision about the estimated threshold from the Probit analysis. The blue line in the plot represents predicted probabilities from the Probit analysis.
Figure 38. Plots of Probit analysis for the iCAM: Subject one (left), Subject two (right), * (data points), blue line (predicted probabilities), green and red lines (lower and upper Fiducial limits respectively).
The threshold results are shown in Table 3. The threshold results of two subjects show similarity in their detectability of noise-targets. The threshold was set at the corrected 50% probability of detection. Lower thresholds indicate better detection of the noise at small amplitudes. As it is illustrated by the Table 3 and Figure 39, the results are different depending on the target size and location. There is no clear correspondence between these threshold values and the results from paired-comparison experiments. For the high-tone area, the Local Sigmoid method has the best detectability with low threshold value and the Zone System was the worst, which is somewhat opposite from the paired-comparison results. However, for the mid- and dark-tone area, the Zone System and the Local Sigmoid method shows the best detectability with the lowest threshold values and the Linear and the Spiral method shows the highest threshold values representing the worst detectability. These results are closely coinciding with the scientific usefulness paired-comparison results. In general, the effects seen with the targets embedded in mid- and dark-tone area have smaller thresholds, are more similar to each across algorithm than the high-tone region target, and closely correspond with the results of scientific usefulness paired-comparison experiment.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Subject 1</th>
<th>Subject 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>High</td>
<td>Mid</td>
</tr>
<tr>
<td>Linear</td>
<td>42.83</td>
<td>21.81</td>
</tr>
<tr>
<td>iCAM</td>
<td>70.77</td>
<td>14.44</td>
</tr>
<tr>
<td>Sigmoid</td>
<td>41.89</td>
<td>16.99</td>
</tr>
<tr>
<td>Spiral</td>
<td>34.79</td>
<td>17.87</td>
</tr>
<tr>
<td>Local Sigmoid</td>
<td>16.55</td>
<td>8.67</td>
</tr>
<tr>
<td>Local Correction</td>
<td>90.64</td>
<td>15.11</td>
</tr>
<tr>
<td>Bilateral</td>
<td>71.77</td>
<td>12.02</td>
</tr>
<tr>
<td>Zone System</td>
<td>87.75</td>
<td>11.15</td>
</tr>
<tr>
<td>PhotoShop</td>
<td>32.86</td>
<td>15.41</td>
</tr>
</tbody>
</table>

Table 3. Results of target detect experiment. Threshold was set at 50% of probability.
Figure 39. Bar graph of target detection experiment results; Subject one (top), Subject two (bottom)
Chapter 7

CONCLUSION

High dynamic range imaging is a very attractive way of capturing real world appearances, since it allows the preservation of complete information on luminance values in the scene. Nine operators used for the display of HDR pictorial imagery were applied to the display of non-pictorial image from a variety of scientific imagery. The underlying principle is that by applying these same HDR operators developed for pictorial imagery, more information can be conveyed because local perceptual contrast in a wider range of the scene is preserved by automatically adjusting the luminance in the image based on the image content.

Two paired-comparison psychophysical experiments were performed to evaluate which algorithms produced the most preferred images and images that were considered scientifically useful. Although the Zone System has the best performance on both average preference and scientific usefulness, the results of the paired-comparison experiments suggest that different encoding schemes might be useful depending on the data type. There was little correlation between preference and scientific usefulness indicating that observers used different criteria for the two tasks. Although the results of the paired comparison analysis was once doubted by the results of goodness-of-fit test, the dual scaling analysis and variance plots provided the evidence that Thurstone’s Law is applicable for both preference and scientific usefulness experiments. To further explicate the success of HDR rendering on these data, the experiment was performed with
radiologists evaluating the rendered Medical images and the results were compared. The results of the dual scaling analysis indicated that there is no significant difference in their opinion. Both radiologists and non-radiologists judged the Medical image rendered by the Zone System as having the highest quality for scientific usefulness when compared to the other operators.

The effects of image distortion introduced by the rendering operators in the third experiment were investigated using a noise target threshold detection paradigm. The magnitudes of the noise-targets were set optimally for each algorithm. The results of high-tone area target indicate that the detectability does not strictly correspond with the results of the paired-comparison experiment. However, the threshold results of mid- and dark-tone area target show somewhat close relationship with the scientific usefulness paired-comparison experiment.
Chapter 8

IMPROVEMENTS AND FUTURE RESEARCH

There is still much work needed to be done in this area. More research is necessary in the area of human visual system in order to further improve the perceptual rendering of HDR scene. Modeling the characteristics of human visual system for the purpose of perceptually accurate tone mapping is complex because the retina adapts locally and the state of adaptation changes continuously by the eye movement. Also, there are many factors influencing human perception that are not completely understood and the model is far too complicated for common use. One significant improvement needed is to develop a more simple, robust, and effective human perceptual model.

The final goal of this research would be to develop the perceptually based schemes for encoding scientific imagery that facilitate its interpretation, considering the visualization of multidimensional nature of the data. In this regards, complete research is required on exploiting rules and techniques for the display of multidimensional graphical information, as well as how to use color appropriately as a tool. Because of the dependence of image type on the results, it seems likely that expert observers may have different criteria for scientific usefulness than novices. Therefore more research using experts is recommended. Both task dependent and image dependent relationships are likely to exist in the rendering of scientific imagery.
Using the results of this research as a benchmark, future experiment can be conducted involving other operators (especially, those with spatially varying mapping functions) and might be beneficial to include more images with various histogram distributions. The search and development is necessary for better models that mimic human perception and facilitates better data mining and interpretation.
REFERENCES


Wright W. D., Why and how chromatic adaptation has been studied, Color Res. Appl. 6, 147-152 (1981).


Cartesian Coordinate System

**APPENDICES**

**APPENDIX 11.1 Matlab Code for each algorithm**

**LINEAR MAPPING**

clear all; close all;

% GUI for opening the image file
[filename, path] = uigetfile("*.bin;*.dat;*.img", 'Select a Image to be processed');
prompt = {'Enter the width of image', 'Enter the length of image'};
name = 'Specifying image size';
lines = 1;
def = {'256', '256'};
selection = inputdlg(prompt, name, lines, def);

disp('********** Linear compression is in process **********')

buffer = pwd;
cd (path);

fid = fopen(filename, 'r');
img = fread(fid, [str2double(selection(1)) str2double(selection(2))], 'uint16');
fclose(fid);

% Linear – straight to RGB digital count
% raw data to RGB - stright linear
% DC = img/max(max(img))*255;
% DC = uint8(DC);
% figure; imshow(DC); title('raw RGB');

% raw data to RGB with gamma correction
load('lcd_parameters'); % load lcd characteristic
DC_gamma = invLUT(img, lcd_parameters); % gamma correction
DCout_gamma = uint8(DC_gamma);
figure; imshow(DCout_gamma); title('Linear');
clear all; close all;

% load image
[filename, path] = uigetfile('*.bin;*.dat;*.img', 'Select a Image to be processed');
prompt = {'Enter the width of image', 'Enter the length of image'};
name = 'Specifying image size';
lines = 1;
def = {'256', '256'};
selection = inputdlg(prompt, name, lines, def);

disp('********** Sigmoid compression is in process **********')
buffer = pwd;
cd (path);

fid = fopen(filename, 'r');
img = fread(fid, [str2double(selection(1)) str2double(selection(2))],'uint16');
fclose(fid);
cd (buffer);

% perform linear compression
lin = img.^((1/2.2));
lin = lin/max(max(lin));
lin = uint8(lin*255);
% figure; imshow(lin); title('Linear & Gamma');

% create L* LUT ranging from 0 to 100 in equal interval
L_lut = [0:100/max(max(img)):100];

% reshape the image
imgSize = size(img);
img = reshape(img, imgSize(1)*imgSize(2), 1);

% get histogram of the image and the cumulative histogram
ha = hist(img, max(img));
% figure; plot(ha)
ha1 = ha(2:end); % histogram without the background
% figure; plot(ha1);
cum = cumsum(ha) - ha(1);
% figure; plot(cum)

% find the corresponding lightness values for the 75% points of the
% cumulative lightness histogram
x = max(cum)*.75; % + ha(1);
temp = [0:100/(max(cumsum(ha))-1):100];

% set the sigmoid parameters (x0(mean) & v(variance))
x0 = temp(round(x));
x_lut = [71.9 60.6 47.5];
sigma = [47.5 34.5 22.0];
v = interp1(x_lut, sigma, x0, 'linear', 'extrap');
% sigmoid function
S = cumsum(1/(sqrt(2*pi)*v)*exp(-(L_lut - x0).^2/(2*v^2)));  
S_lut = S/max(S)*100;

% figure; plot(S_lut);
L_out = S_lut(img+1);

% apply monitor gamma correction
load('lcd_parameters');
DCout = gammaLUT(L_out, lcd_parameters);

% reshape the image to original shape
outImage = reshape(DCout, imgSize(1), imgSize(2));
outImage = uint8(outImage);

% display image
figure; imshow(outImage); title('Sigmoid')

**LOCALIZED Sigmoid MAPPING**

clear all; close all;

% load image
[filename, path] = uigetfile('*.bin;*.dat;*.img', 'Select a Image to be processed');
prompt = {'Enter the width of image', 'Enter the length of image'};
name = 'Specifying image size';
lines = 1;
def = {'256', '256'};
selection = inputdlg(prompt, name, lines, def);

disp('********** Local Sigmoid Mapping is in process **********)

buffer = pwd;

fid = fopen(filename, 'r');
img = fread(fid, [str2double(selection(1)) str2double(selection(2))], 'uint16');
close(fid);

cd (buffer);

% get blurred version (Gussian blur) of the image
imSize = size(img);
xDim = imSize(2);
yDim = imSize(1);

[x,y] = meshgrid(1:xDim, 1:yDim);
distMap = sqrt(x.^2 + y.^2);

% distMap = idl_dist(yDim,xDim);
kernel = exp(-1*(distMap/3).^2);

filter = max(real(fft2(kernel)),0);
filter = filter./filter(1,1);
imgblur = zeros(size(img));

imgblur = max(real(ifft2(fft2(img).*filter)),0);

% % display blurred image
% outblur = imgblur/max(max(imgblur));
% figure; imshow(outblur); title('blurred image');

img = reshape(img, imSize(1)*imSize(2), 1);
imgmask = reshape(imgblur, imSize(1)*imSize(2), 1);

% local sigmoid function
x0 = imgmask;
sigma = mean(img);
imlut = linspace(min(img), max(img), max(img)+1);

% create sigmoid for each pixel
localsig = zeros(size(img));
for i = 1:size(img,1);
    expofun = exp(-(imlut - x0(i)).^2/(2*sigma.^2));
    sig = cumsum((1./(sqrt(2*pi)*sigma)).*expofun);
    localsig(i) = sig(img(i)+1);
end

% display raw processed image
outsig = reshape(localsig, imSize(1), imSize(2));
% figure; imshow(outsig); title('Local Sigmoid');

% apply gamma correction
load('lcd_parameters');
outsig = outsig/max(max(outsig));
Sigout = gammaLUTsig(outsig, lcd_parameters2);

% display local-sigmoid image
OutSig = (Sigout - min(Sigout(:))) ./ (max(Sigout(:)) - min(Sigout(:)));
OutSig = uint8(255*OutSig);
figure; imshow(OutSig); title('Local Sigmoid');

**Spiral Rendering**

clear all; close all;

[filename, path] = uigetfile(’*.bin;*.dat;*.img’, ’Select a Image to be processed’);
prompt = {’Enter the width of image’,’Enter the length of image’};
name = ’Specifying image size’;
lines = 1;
def = {’256’, ’256’};
selection = inputdlg(prompt,name,lines,def);

disp(’*********** Spiral is in process ***********’)

106
buffer = pwd;
cd (path);

fid = fopen(filename, 'r');
img = fread(fid, [str2double(selection(1)) str2double(selection(2))], 'uint16');
fclose(fid);

cd (buffer);

% create L* LUT, C* LUT, and H* LUT
Num_loops = 1.25; % assign number of loops
start_h = 180; % start angle of loop
L_lut = linspace(0, 100, max(max(img)) + 1); % ranging from 0 to 100 in equal interval
C_lut = 148 * ((L_lut(100) - (L_lut(100)).^2);
H_lut = linspace(start_h, 360 * Num_loops + start_h, max(max(img)) + 1);

% orginal algorithm (by ethan)
% % 360deg hue rotation and create C* and H* LUT
% Num_loops = 1.25; % assign number of loops
% start_h = 180; % start angle of loop
% H_lut = [(0 + start_h):(360 * Num_loops)/(max(max(img))):(360 * Num_loops) + start_h];
% x = [0:1/(max(max(img))):1];
% y = 148 * ((L_lut./100) - (L_lut./100).^2); % maximize depending on number of loops (same as y = 37 * 4 * (-1 * (x -.5).^2 + .25));
% C_lut = y;

% ==============================================================
% Calculate deltaE along the scale
% check the color difference between each step
a_lut = C_lut.*cos(H_lut.*pi./180);
b_lut = C_lut.*sin(H_lut.*pi./180);

% Lab1 = [L_lut(1:end-1); a_lut(1:end-1); b_lut(1:end-1)];
% Lab2 = [L_lut(2:end); a_lut(2:end); b_lut(2:end)];
%
% % DE00 = deltaE00(Lab1, Lab2);
% % DE94 = deltaE94(Lab1, Lab2);
% % figure; plot(DE00)
% % hold on;
% % figure; plot(DE94(2:end-1), 'r');
% % figure; plot(DEab);
% % hold off;
% ==============================================================

% reshape the image to make it easier to covert digital value to L* value
imgSize = size(img);
img = reshape(img, imgSize(1)*imgSize(2), 1);

% assign corresponding L*, C*, h* value to each Digital value of the image
L_star = L_lut(img + 1);
C_star = C_lut(img + 1);
H_star = H_lut(img + 1);

% Transform image from LCH space to Lab space
a_star = C_star.*cos(H_star.*pi./180); % angles are in radians.
\[ b_{\text{star}} = C_{\text{star}} \cdot \sin(H_{\text{star}} \cdot \pi / 180); \]

% Transform Lab space to XYZ tristimulus value
% white point (XYZ White point) of the display is needed
XYZWhite = [117.6, 131.8, 141.0]; % white measurement of the display

XYZ = LabtoXYZ(L_star, a_star, b_star, XYZWhite);

% apply inverse display characteristic
load('lcd_parameters');
[DCout, outofgamut] = lcd_inverse_model(XYZ, lcd_parameters);

DCout = reshape(DCout', imgSize(1), imgSize(2), 3);
DCout = uint8(DCout);
figure; imshow(DCout); title('Spiral')

LOCAL COLOR CORRECTION

clear all; close all;

% load image
[filename, path] = uigetfile('*.bin;*.dat;*.im', 'Select a Image to be processed');
prompt = {'Enter the width of image','Enter the length of image'};
name = 'Specifying image size';
lines = 1;
def = {'256', '256'};
selection = inputdlg(prompt, name, lines, def);
derelaxing ********** Local Contrast is in process **********

buffer = pwd;
cd (path);

fid = fopen(filename, 'r');
img = fread(fid, [str2double(selection(1)) str2double(selection(2))],'uint16');
fclose(fid);

cd (buffer);

% apply log to input value
img = max(img, 1);
img = log(img);

% get localized contrast function using blurred version (Gussian blur) of the image
imSize = size(img);
xDim = imSize(2);
yDim = imSize(1);

[x,y] = meshgrid(1:xDim, 1:yDim);
distMap = sqrt(x.^2 + y.^2);
kernel = exp(-1*(distMap./15).^2);
filter = max(real(fft2(kernel)),0);
filter = filter./filter(1,1);

imgblur = zeros(size(img));

imgblur = max(real(ifft2(fft2(img).*filter)),0);

% inverting the blurred image
mask = max(max(imgblur))-imgblur;
maskout = mask/max(max(mask));
% figure; imshow(maskout); title('Mask');

% get local contrast (Moroney)
maxmask = max(max(mask));
meanmask = mean(mean(mask));
% out = max(max(img))*(img/max(max(img))).^((maxmask-mask)/meanmask));
out = (img/max(max(img))).^((maxmask-mask)/meanmask));
Localcont = exp(out);

% apply monitor gamma correction
load('lcd_parameters');
% localimg = reshape(localimg, size(localimg,1)*size(localimg,2));
DCout = gammaLUT(Localcont,lcd_parameters);

% display image
DCout = (DCout - min(DCout(:))) / (max(DCout(:)) - min(DCout(:)));
DCout = uint8(DCout*255);
figure; imshow(DCout); title('LocalCont & Gamma');

iCAM

clear all; close all

[filename, path] = uigetfile('*.bin;*.dat;*.img', 'Select a Image to be processed');
prompt = {'Enter the width of image','Enter the length of image'};
name = 'Specifying image size';
lines = 1;
def = {'256', '256'};
selection = inputdlg(prompt,name,lines,def);

disp('********** iCAM is in process **********')

buffer = pwd;
cd (path);

fid = fopen(filename, 'r');
img = fread(fid, [str2double(selection(1)) str2double(selection(2))],'uint16');
% fid = fopen(filename, 'r', 'b');
% img = fread(fid, [str2double(selection(1)) str2double(selection(2))],'uint16');
fclose(fid);

cd (buffer);
% function iCAM(filename)

% change this line to alter the Fl function
hdrlm = img/max(img(:));
% green = squeeze(hdrlm(:,:,2)) ;
green = hdrlm;
prc = prctile(green(:), 99) ;
k = 25;
scale = k/prc;
hdr_image = render_hdr(hdrlm*scale) ;

% Display the image, for viewing glory
figure; imshow(hdr_image); title('iCAM');
figure; imshow(hdr_image(:,:,2));

%******************************************************************************
function outlmage = render_hdr(imageln)

% Written by: Garrett M. Johnson
%
% This function performs the "meat" of the iCAM
% High-Dynamic Range tone mapping. It is passed
% a floating point RGB image
%
% Modified: 02/12/04
%
% Transform to XYZ space
lcd = load ('lcd_parameters.mat');
lcd_parameters = lcd.lcd_parameters2;
imageln = repmat(imageln,[1 1 3]);
size_img = size(imageln);
scalars = reshape(imageln, size_img(1)*size_img(2), size_img(3));
XYZpred = (scalars * (lcd_parameters.primaries'));
xyzlmage = reshape(XYZpred, size_img(1), size_img(2), size_img(3));

% perform the forward iCAM hdr transform
icamlmage = iCam_hdr(xyzlmage);
clear xyzlmage;

% Invert the IPT transform
icamXYZ = inv_ipt(icamlmage);
clear icamlmage;

% Invert the chromatic adaptation transform
icamXYZa = inv_cat(icamXYZ);
clear icamXYZ;

% LCD inverse model
led_Y = 131;

% Find the 0.99 percentile (or quartile)
% perc = prctile(icamXYZa(:,),99);
% % clip the image to the 0.99 percentile
% icamXYZa = min(icamXYZa,perc);
k = lcd_Y/\max(\max(icamXYZa(:,:,2))); 
outImage = uint8(XYZimage_lcd_inv_model(icamXYZa*k, lcd_parameters)); 

function imgIPT = iCam_hdr(imageIn)
% written by: Lawrence Taplin and Garrett M. Johnson
% The function essentially performs the "meat" of the iCAM
% HDR tone mapping. It is given an XYZ image as the input
% and returns an IPT image as the output
% Modified: 01/31/02
%
% get the adaptation "whitepoint," which is a blurred version
% of the image

imSize = size(imageIn);
xDim = imSize(2);
yDim = imSize(1);

%distMap = dist(xDim, yDim);
distMap = idl_dist(yDim, xDim);
kernel = exp(-1*(distMap./(xDim/4)).^2);
% since we are convolving, normalize the kernel to sum
% to 1, and shift it to the center
% kernel = shift(kernel, xDim/2, xDim/2)/total(kernel)

filter = max(real(fft2(kernel)),0);
filter = filter./filter(1,1);

% kernel = kernel/kernel[0,0]
whiteXYZ = zeros(size(imageIn));

%whiteXYZ[0,*,*] = convol(reform(image[1,*,*]), kernel, /center, /edge_wrap)
whiteXYZ(:,:,1) = max(real(ifft2(fft2(imageIn(:,:,2)).*filter)),0);
whiteXYZ(:,:,2) = whiteXYZ(:,:,1);
whiteXYZ(:,:,3) = whiteXYZ(:,:,1);

% figure;
% imagesc(whiteXYZ);

% surface, kernel
% tvscl, whiteXYZ, /true
% perform the HDR hromatic adaptation transform
imgCAT = cat_hdr(imageIn, whiteXYZ);

%imgCAT = image

% transform into the IPT color space, blurred appropriately
imgIPT = ipt_hdr(imgCAT, squeeze(imageIn(:,:,1)));
function a = idl_dist(m,n);

% Written by: Lawrence Taplin
%
% Pretty much a direct port of the IDL
% Dist function...
%
% x=findgen(n); Make a row
% x = (x < (n-x)) ^ 2 ; column squares
% if n_elements(m) le 0 then m = n
%
% a = FLTARR(n,m,/NOZERO); Make array
%
% for i=0L, m/2 do begin ; Row loop
% y = sqrt(x + i^2); Euclidian distance
% a[0,i] = y ; Insert the row
% if i ne 0 then a[0, m-i] = y; Symmetrical
% endfor
% return,a

x=0:(n-1); % Make a row
x = min(x,(n-x))^2; % column squares
if nargin ==1
  m = n;
end

a = zeros(m,n); % Make array

for i=0:m/2 % Row loop
  y = sqrt(x + i^2); % Euclidian distance
  a(i+1,:) = y; % Insert the row
  if i ~ 0
    a(m-i+1,:) = y; % Symmetrical
  end
end

%******************************************************************************
function XYZ_adapt = Cat_hdr(image, whitepoint)

% function cat_hdr(image, whitepoint)
%
% written by: lawrence taplin and garrett m. johnson
%
% perform a high-dynamic range chromatic adaptation transform
% for the ICAM image appearance model.
%
% Note: this isn't so much a chromatic adaptation as a luminance
% adaptation, since we are normalizing all the tristimulus
% values with a single number (Y).
%
% Last modified: 01/31/02
%
% First things first...define the XYZ to RGB transform
M = [ [0.7328, 0.4296, -0.1624];...
    [-0.7036, 1.6974, 0.0061];...
    [0.0030, 0.0136, 0.9834] ];

Mi = inv(M);

% set teh whitepoint for D65, as that is where "IPT" is
% defined
xyz_d65 = [ 95.05, 100.0, 108.88];

RGB_image = changeColorSpace(image, M);
RGB_white = changeColorSpace(whitepoint, M);

% do a little normalization on the units
RGB_white = RGB_white*max(RGB_image(:))/max(RGB_white(:));
RGB_d65 = changeColorSpace(xyz_d65, M);

% uncomment the following line to use the incomplete adaptation
% from CIECAM02
%
% D = F - ( F / (1 + 2*(luminance^1.0/4.0) + (luminance^2.0)/300.0 ) )
% otherwise, manually set a degree of adaptation, such as 0.1 for
% 10 percent
D = 0.3;

% perform the chromatic adaptation
Rc = (D * RGB_d65(:,:,1)) / RGB_white(:,:,1) + (1 - D) .* RGB_image(:,:,1);
Gc = (D * RGB_d65(:,:,2)) / RGB_white(:,:,2) + (1 - D) .* RGB_image(:,:,2);
Bc = (D * RGB_d65(:,:,3)) / RGB_white(:,:,3) + (1 - D) .* RGB_image(:,:,3);

imSize = size(image);
xDim = imSize(2);
yDim = imSize(1);

adaptImage = zeros(yDim, xDim, 3);

adaptImage(:,:,1) = Rc;
adaptImage(:,:,2) = Gc;
adaptImage(:,:,3) = Bc;

XYZ_adapt = changeColorSpace(adaptImage, Mi);

%****************************************************************************************
% Written by: Lawrence Taplin and Garrett M. Johnson
% Based on scielab procedure of Wandell and Zhang
% The input image consists of three input images, say R,G,B, joined as
% inImage = [ R G B];
% The output image has the same format
% The 3 x 3 color matrix converts column vectors in the input image
% representation into column vectors in the output representation.
% Modified: 03/18/01
% Insured the input image is put back into the same format as it was passed.

inSize = size(inImage);

% We put the pixels in the input image into the rows of a very
% large matrix
% if length(inSize)==3
  inImage = reshape(inImage, inSize(1)*inSize(2),inSize(3));
end

% We post-multiply by colorMatrix to convert the pixels to the output
% color space
% outlmage = inImage*colorMatrix;

% Now we put the output image in the basic shape we use
% if length(inSize)==3
  inImage = reshape(inImage, inSize(1),inSize(2),inSize(3));
  outlmage = reshape(outlmage, inSize(1),inSize(2),inSize(3));
end

function ipt_image = ipt_hdr(xyz_image, Yimage)

% Written by: Garrett M. Johnson
% This function performs the IPT transform
% Specifically for the HDR iCAM model. Essential
% It creates a low-pass image mask based on the Y
% channel, and uses the CIECAM02 surround formula
% to modify the IPT exponent
% Modified 02/02/03

imSize = size(xyz_image);
xDim = imSize(2);
yDim = imSize(1);

distMap = idl_dist(yDim, xDim);

% The kernel is a Gaussian function of width
% xDimension/3.0
%% kernel = \exp(-1 \cdot \frac{\text{distMap}}{\text{xDim}/3})^2; 
kernel = kernel/kernel(1,1);

% Transform Gaussian to Frequency domain, and normalize 
% the DC component 
filter = \max(\text{real}(\text{fft2}(\text{kernel})), 0); 
filter = filter/filter(1,1);

% Filter the image 
yLow = \max(\text{real}(\text{ifft2}(\text{fft2}(Yimage).\text{filter})), 0);

iptMat = [ [0.4000, 0.4000, 0.2000];...
[4.4550,-4.8510, 0.3960];...
[0.8056, 0.3572,-1.1628] ];

xyz2lms = cmatrix('xyz2lms');

Ims_image = \text{changeColorSpace}(xyz_image/100.0, xyz2lms);

% the exponent scale is calculated based on the surround 
% function from CIECAM02. It is set to 1.0 for a value 
% of 100.0 
\text{a} = 1.7; 
\text{b} = 5; 
exp_scale = (1/\text{a}) \cdot (0.2 \cdot (1/(\text{b} \cdot \text{yLow} + 1)).^4 \cdot (\text{b} \cdot \text{yLow} + 0.1*(1-(1/(\text{b} \cdot \text{yLow} + 1)).^4).^2 \cdot (\text{b} \cdot \text{yLow}).^4(1/3));

lms_nl = Ims_image;

% figure; hist(yLow(:),1000)

% apply the IPT exponent along with the scaling factor 
lms_nl(:,:,1) = abs(Ims_image(:,:,1)).^\text{exp_scale}.43;
lms_nl(:,:,2) = abs(Ims_image(:,:,2)).^\text{exp_scale}.43;
lms_nl(:,:,3) = abs(Ims_image(:,:,3)).^\text{exp_scale}.43;

ipt_image = \text{changeColorSpace}(lms_nl, iptMat);

%**********************************************************************************************************************
% function result = cmatrix(matrixtype, spacetype)
%
% written by: Lawrence Taplin and Garrett Johnson 
%
% Based on the scielab code from Wandell and Ziang 
%
% Returns a 3x3 color matrix used by changeColorSpace. 
%
% matrixtype has the following options: 
% 'lms2opp' -- cone coordinate to opponent (Poirson & Wandell 1993) 
% 'opp2lms' -- inverse of the above matrix
% 'xyz2opp' -- xyz to opponent (CIE1931 2 degree XYZ)
% 'opp2xyz' -- inverse of the above matrix
% 'lms2xyz' -- Hunt-Pointer-Estevez transformation from cone
% to XYZ, normalized for D65 (lms=[100 100 100] for D65).
% 'xyz2lms' -- inverse of lms2xyz.
% 'xyz2yiq' -- convert from XYZ to YIQ
% 'yiq2xyz' -- inverse of the above matrix
% 'rgb2yuv' -- convert from RGB to YUV (YCbCr) for JPEG compression
% 'yuv2rgb' -- inverse of the above matrix
% 'xyz2srgb' -- from XYZ to sRGB values
% 'srgb2xyz' -- inverse of the above matrix
% (the above are not dependent on device calibration)
%
% 'rgb2lms' -- monitor rgb to cone coordinate
% 'lms2rgb' -- inverse of the above matrix
% 'rgb2xyz' -- rgb to xyz 2 degree.
% 'xyz2rgb' -- inverse of the above matrix
%
% spacetype specifies what type of xyz space (CIE1931 2 degree or
% CIE1964 10 degree) is required.
% spacetype = 2: cie1931 2 degree XYZ (default)
% spacetype = 10: cie1964 10 degree XYZ
%
if (nargin == 2)
    spacetype = 2;
end

switch matrixtype
    case 'lms2opp',
        result = inv([ [0.9900, -0.1060, -0.0940];
                        [-0.6690, 0.7420, -0.0270];
                        [-0.2120, -0.3540, 0.9110] ]);  
        result = [ [2.0, 1.0, 0.05];...
                    [1.0, -1.09, 0.09];...
                    [0.11, 0.11, -0.22] ];
    case 'opp2lms',
        result = inv([ [0.9900, -0.1060, -0.0940];
                        [-0.6690, 0.7420, -0.0270];
                        [-0.2120, -0.3540, 0.9110] ]);  
    case 'lms2xyz',
        result = inv([ [.4002, .7076, -.0808];....
                        [-.2280, 1.15, .0612];...
                        [.0, .0, .9184] ]);
    case 'xyz2lms',
        result = [ [.4002, .7077, -.0807];....
                    [-.2280, 1.1500, .0612];...
                    [.0, .0, .9184] ];
case 'xyz2opp',
  if (spacetype == 2)
    result = ([ 278.7336, 721.8031, -106.5520];
               -448.7736, 289.8056,  77.1569];
               85.9513, -589.9859, 501.1089]) / 1000.0;
  else
    result = ([ 288.5613, 659.7617, -130.5654];
               -464.8864, 326.2702,  62.4200];
               79.8787, -554.7976, 481.4746]) / 1000;
end

case 'opp2xyz',
  if (spacetype == 2)
    result = inv([ 278.7336, 721.8031, -106.5520];
               -448.7736, 289.8056,  77.1569];
               85.9513, -589.9859, 501.1089]) / 1000.0);
  else
    result = inv([ 288.5613, 659.7617, -130.5654];
               -464.8864, 326.2702,  62.4200];
               79.8787, -554.7976, 481.4746]) / 1000;
end

case 'xyz2yiq',
  result = [ 0.0, 1.0000, 0.0];
           [1.4070, -0.8420, -0.4510];
           [0.9320, -1.1890, 0.2330];

case 'yiq2xyz',
  result = inv([ 0.0, 1.0000, 0.0];
              [1.4070, -0.8420, -0.4510];
              [0.9320, -1.1890, 0.2330]);

case 'rgb2yuv',
  result = [ 0.299, 0.587, 0.114];
           [-0.1687,-0.3313, 0.5];
           [0.5, -0.4187, -0.0813];

case 'yuv2rgb',
  result = inv([ 0.299, 0.587, 0.114];
               [-0.1687,-0.3313, 0.5];
               [0.5, -0.4187, -0.0813]);

case 'xyz2srg',
  result = [ 0.03241, -.015374, -0.004986];
           [-0.009692, .018760, 0.000416];
           [0.000556, -0.002040, .01057];

case 'srgb2xy',
  result = inv([ 0.03241, -.015374, -0.004986];
               [-0.009692, .018760, 0.000416];
               [0.000556, -0.002040, .01057]);
case 'rgb2lms',
    result = [[12.2430,  44.4548,   6.5701];
              [4.6321,   44.6748,   9.5109];
              [0.5227,   4.6900,   44.8061]];

case 'lms2rgb',
    result = inv([[12.2430,  44.4548,   6.5701];
                   [4.6321,   44.6748,   9.5109];
                   [0.5227,   4.6900,   44.8061]]);

% be advised...add in your own matrix here!!!!!
case 'rgb2xyz',
    if (spacetype == 2)
        result = [[41.384, 22.155, .487];
                   [25.053, 51.424, 5.438];
                   [11.014, 9.743, 56.089]];
    else
        result = [[17.4665, 27.7468, 16.5398];
                   [10.0969, 48.1835, 11.6466];
                   [0.9293,  7.3710, 85.5683]];
    end

case 'xyz2rgb',
    if (spacetype == 2)
        result = inv([[41.384, 22.155, .487];
                       [25.053, 51.424, 5.438];
                       [11.014, 9.743, 56.089]]);
    else
        result = inv([[17.4665, 27.7468, 16.5398];
                        [10.0969, 48.1835, 11.6466];
                        [0.9293, 7.3710, 85.5683]]);  
    end

otherwise
    result = 0;
end

result = result';

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

function xyz_image = inv_ipt(ipt_image)

% Written by: Lawrence Taplin and Garrett M. Johnson
%
% This function inverts the IPT transform for display
%
% It uses a single number (0.43) for the inversion rather
% than a spatially localized low-pass mask.
%
% imSize = size(ipt_image)
imSize = size(ipt_image);
xDim = imSize(2);
yDim = imSize(1);
inv_iptMat = inv([ [ 0.4000, 0.4000, 0.2000];...
[ 4.4550,-4.8510, 0.3960];...
[ 0.8056, 0.3572,-1.1628]]);

Ims2xyz = cmatrix('lms2xyz');

Ims_image = changeColorSpace( ipt_image, inv_iptMat );

xyz_image = changeColorSpace(abs(Ims_image).^(1/43), Ims2xyz);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

function XYZ_adapt = inv_Cat(imageIn)

% written by: Lawrence Taplin and Garrett M. Johnson
%
% function to invert the chromatic adaptation transform from
% D65 to the "monitor" white so it can be displayed on the "tv."
% Note that in the iCAM framework the inverse transform
% is done with a single number
%
% Modified: 01/31/03

% First things first...define the XYZ to RGB transform
% again using the CIECAM02 transform
M = [ [ 0.8562, 0.3372,-0.1934];...
[-0.8360, 1.8327, 0.0033];...
[ 0.0357, -0.0469, 1.0112] ];

Mi = inv(M);

xyz_d65 = [ 95.05, 100.0, 108.88];
%whitepoint = [100.0, 100.0, 100.0];
whitepoint = [95.047, 100.0, 108.883];
%whitepoint = 100*[116.44/130.94, 130.94/130.94, 138.18/130.94];

RGB_image = changeColorSpace(imageIn, M);
RGB_white = changeColorSpace(whitepoint, M);
RGB_d65 = changeColorSpace(xyz_d65, M );

% we want to use a complete adaptation transform, so
% keep D set to 1.0, and don't try to calculate it
D = 1;

Rc = (D * RGB_white(1) ./ RGB_d65(1) + 1 - D) .* RGB_image(:,:,1);
Gc = (D * RGB_white(2) ./ RGB_d65(2) + 1 - D) .* RGB_image(:,:,2);
Bc = (D * RGB_white(3) ./ RGB_d65(3) + 1 - D) .* RGB_image(:,:,3);

imSize = size(imageIn);
xDim = imSize(2);
yDim = imSize(1);

adaptImage = zeros(yDim, xDim,3);
adaptImage(:,:,1) = Rc;
adaptImage(:,:,2) = Gc;
adaptImage(:,:,3) = Bc;

XYZ_adapt = changeColorSpace(adaptImage, Mi);

**Fast Bilateral Filtering**

clear all; close all;

[filename, path] = uigetfile("*.bin;*.dat;*.img", 'Select a Image to be processed');
prompt = {'Enter the width of image', 'Enter the length of image'};
title = 'Specifying image size';
lines = 1;
def = {'256', '256'};
selection = inputdlg(prompt, title, lines, def);

disp('*********** Bilateral mapping is in process **********')

buffer = pwd;
cd (path);

fid = fopen(filename, 'r');
img = fread(fid, [str2double(selection(1)) str2double(selection(2))], 'uint16');
close(fid);

cd (buffer);

% normalize the image and make it 3 channel
% img = img./max(max(img))*100;
% img = repmat(img,[1 1 3]);

outimg = DorseyBilateral(img,5); % base contrast of 5 recommended
% out_image = img.*outimg;

% apply inverse display model and gamma correction
outimg = (outimg - min(outimg(:)))./(max(outimg(:)) - min(outimg(:)));
load('lcd_parameters');
DCout = gammaLUT(outimg, lcd_parameters);
outDC = (DCout - min(DCout(:)))./(max(DCout(:)) - min(DCout(:)));
outDC = uint8(outDC*255);
figure; imshow(outDC);

% ****************************______________________________Function ____________________________
function outimg = DorseyBilateral(imageIn,base_contrast)

%Get size info.
imSize = size(imageIn);
xDim = imSize(2);
yDim = imSize(1);
% Separating RGB into Color and intensity
% intensity = imageln;
% intensity(:,:,1)=1/6*(imageln(:,:,1)*20+imageln(:,:,2)*40+imageln(:,:,3));
% intensity = max(intensity, 0.000000000001);
%
% rimg(:,:,1)=imageln(:,:,1)./intensity(:,:,1);
% gimg(:,:,1)=imageln(:,:,2)./intensity(:,:,1);
% bimg(:,:,1)=imageln(:,:,3)./intensity(:,:,1);
intensity = imageln;
intensity = max(intensity, 1);

logOfint=log(intensity);

%spatial processing (similar to low-pass filter)
baselayer=PiecewiseBilateral(logOfint);

detaillayer=logOfint-baselayer;

% We can modify this section.
compressionfactor=base_contrast/(max(baselayer(:))-min(baselayer(:)));

mL=mean(logOfint(:));
logOfoutint(:,:)=detaillayer+compressionfactor*(baselayer-mL)+mL;

% outimg = logOfoutint;
outimg = exp(logOfoutint);

%reconstruction of color image
% out_image(:,:,1) = rimg(:,:,1).*exp(logOfoutint(:,:,1));
% out_image(:,:,2) = gimg(:,:,1).*exp(logOfoutint(:,:,2));
% out_image(:,:,3) = bimg(:,:,1).*exp(logOfoutint(:,:,3));

function imageOut=PiecewiseBilateral(imageln)

% Get size info.
imSize = size(imageln);
xDim = imSize(2);
yDim = imSize(1);

% Parameters
% Keep sigma_s constant to a value of 2% of the image size
sigma_s=2*xDim/100;
% The value sigma_r=0.4 performed consistently well for all their exp.
sigma_r=0.4;

% Max Min
maxl=max(imageln(:));
minl=min(imageln(:));
nSeg=(maxl-minl)/sigma_r;
inSeg=round(nSeg);
% Create Gaussian Kernel
distMap = idl_dist(yDim,xDim);
kernell = exp(-1*(distMap./sigma_s).^2);
kernell = kernell/kernell(1,1);
fs = max(real(fft2(kernell)),0);
fs = fs./fs(1,1);
% Set the output to zero
imageOut=zeros(size(imageIn));
jG=zeros(size(imageIn));
jK=zeros(size(imageIn));
intW=zeros(size(imageIn));  % Interpolation Weight map

% Go!
for j=0:1:inSeg
    value_i=minl+j*(maxl-minl)/inSeg;
    % edge-stopping function
    jG=exp((-1/2)*((imageIn-value_i)./sigma_r).^2);
    % normalization factor
    jK=max(real(ifft2(fft2(jG(:,:,j)*fs)), 0.0000000001);
    % Compute H for each pixel
    jH=jG.*imageIn;
    sjH=real(ifft2(fft2(jH(:,:,j)*fs)));
    % normalize
    jJ=sjH./jK;
    % interpolation
    intW=max(ones(size(imageIn))-abs(imageIn-value_i)*(inSeg)/(maxl-minl),0)-imageOut(:,:)=imageOut(:,:)+jJ(:,:).*intW(:,:);
end

ZONE SYSTEM

clear all; close all;

[filename, path] = uigetfile("*.bin;*.dat;*.img", 'Select a Image to be processed');
prompt = {'Enter the width of image','Enter the length of image'};
name = 'Specifying image size';
lines = 1;
def = {'256', '256'};
selection = inputdlg(prompt,name,lines,def);

disp('********** Zone System is in process **********)

buffer = pwd;
cd (path);

fid = fopen(filename, 'r');
img = fread(fid, [str2double(selection(1)) str2double(selection(2))],'uint16');
fclose(fid);

cd (buffer);

% convert to luminance
% normalize the image and make it 3 channel
img = img./max(max(img));  % normalize it to 100 for pictorial image
%  % img = max(img,1);
%  % img = log10(img);
%  % % lin = img;
img = img*3;  % set the normalizing factor: 3 for scientific

122
% img = repmat(img,[1 1 3]);

% Zone System
outimg=FerwerdaZone( img , 0.18 , 8.0 . 8 );

% apply gamma correction and display image
imgout = (outimg - min(min(outimg))) ./ (max(max(outimg)) - min(min(outimg)));
% apply monitor gamma correction
load('lcd_parameters');
DCout = gammaLUT(outimg, lcd_parameters);
outDC = (DCout - min(DCout(:))) ./ (max(DCout(:)) - min(DCout(:)));
outDC = uint8(outDC*255);
figure; imshow(outDC); title('Zone System');

% Function Ferwerda Zone

%imageln: Original RGB image [Ysize,Xsize,3]
%a:   Key value. typical=0.18 vary from 0 to 1
% phai: Typically, varying from 0.18(low) to 0.36 and 0.72(high)
%Ns: the number pf scale (Ns was set to 8)

function out_image=FerwerdaZone( imageIn , a , phai , Ns )

%Get size info.
imSize = size(imageIn);
xDim = imSize(2);
yDim = imSize(1);

% Parameters
% phai=8.0;
% a=0.18;
% Ns=8;
epsilon=0.05;
alpha1=0.35;
alpha2=0.35*1.6;
m=1:Ns;
sm=1.6.^((m-1);

% Liminance value is obtained by original RGB
% Limg(:,:,)=0.27*imageIn(:,:,1)+0.67*imageIn(:,:,2)+0.06*imageIn(:,:,3);
Limg = imageIn;

% Gaussian kernel
distMap = idl_dist(yDim,xDim);
flag=zeros(yDim,xDim);  %0:never 1:found
curflag=zeros(yDim,xDim);
preflag=zeros(yDim,xDim);
Ld=zeros(yDim,xDim);
curlD= zeros(yDim,xDim);
preLd=zeros(yDim,xDim);
EPS=ones(yDim,xDim)*epsilon;
% Search the fitting size of sm for each pixel
for j=1:Ns  %Ver002
    R1 = (1/(pi*(alpha1*sm(j)))*exp(-1*(distMap/( alpha1*sm(j) )).^2);
    R2 = (1/(pi*(alpha2*sm(j)))*exp(-1*(distMap/( alpha2*sm(j) )).^2);
    R1 = R1/R1(1,1);
    R2 = R2/R2(1,1);
    fR1 = max(real(fft2(R1)),0);
    fR2 = max(real(fft2(R2)),0);
    fR1 = fR1/fR1(1,1);
    fR2 = fR2/fR2(1,1);
    V1 = max(real(ifft2(fft2(Limg(:,:).*fR1)),0);
    V2 = max(real(ifft2(fft2(Limg(:,:).*fR2)),0);
    V = (V1-V2)./( V1 + (a*(2^phi)) / ((sm(j))));
    curflag=(abs(V)<EPS)&(-flag);
    if j==Ns  %Ver002
        curflag=-flag;
    end
    curLd=(Limg./(1+V1)).*curflag;
    Ld=preLd+curLd;  preLd=Ld;
    flag=preflag|curflag;  preflag=flag;  %0:never 1:found
end
% Limg=max(Limg,0.0000000001);  %to avoid zero-division
out_image = Ld;
% out_image(:,:,1)=(imageIn(:,:,1)./Limg(:,:,1).*Ld(:,:,1);
% out_image(:,:,2)=(imageIn(:,:,2)./Limg(:,:,2).*Ld(:,:,2));
% out_image(:,:,3)=(imageIn(:,:,3)./Limg(:,:,3).*Ld(:,:,3));
Appendix 11.2

The six imageries rendered by nine different operators

Medical (Magnetic Resonance Image)
Hyperspectral (Airborne Visible InfraRed Imaging Spectrometer)
Astronomical (Hubble Space Telescope)
Radar (Airborne Synthetic Aperture Radar)

<table>
<thead>
<tr>
<th>Local Correction</th>
<th>Linear</th>
<th>Local Sigmoid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sigmoid</td>
<td>iCAM</td>
<td>Bilateral Filtering</td>
</tr>
<tr>
<td>Spiral</td>
<td>Zone System</td>
<td>Photoshop</td>
</tr>
</tbody>
</table>
Pictorial (Memorial Church from http://www.debevec.org)
APPENDIX 11.3

Results of paired comparison experiments

Preference Experiment
Scientific Usefulness Experiment

[Diagrams showing perceived image quality across different domains and algorithms]
APPENDIX 11.4

Schematic plots for Preference Experiment
Schematic plots for Scientific Usefulness Experiment

Medical

Hyperspectral

Astronomical

Radar

InfraRed

Pictorial
APPENDIX 11.5  Probit Analysis

*: data points, blue line: predicted probability, green and red lines: lower and upper Fiducial limits respectively

Subject One: High-tone area Target
Subject One: Mid-tone area Target
Subject One: Dark-tone area Target
Subject Two: High-tone area Target
Subject Two: Mid-tone area Target

![Graphs for Subject Two: Mid-tone area Target]
Subject Two: Dark-tone area Target