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Automated detection of effective scene illuminant chromaticity from specular highlights in digital images

Wayne Richard

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AUTOMATED DETECTION OF EFFECTIVE 
SCENE ILLUMINANT CHROMATICITY FROM 
SPECULAR HIGHLIGHTS IN DIGITAL IMAGES

by

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

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by

Wayne M. Richard

Submitted to the
Center for Imaging Science
in partial fulfillment of the requirements
for the Master of Science Degree
at the Rochester Institute of Technology

Abstract

An advanced, automated method is presented for determining an effective scene illuminant chromaticity (scene illuminant plus imaging system variables) from specular highlights in digital images subsequent to image capture. Underlying theories are presented based on a two component reflection model where the scene illuminant relative spectral power distribution is preserved in the specular component. Related methodologies for extracting scene illuminant information as well as alternative methods for achieving color constancy are presented along with factors which inhibit successful implementation. Following, development of a more robust algorithm is discussed. This algorithm is based on locating the center of convergence of a radial line pattern in the two-dimensional chromaticity histogram which theoretically identifies the effective scene illuminant chromaticity. This is achieved by using a radiality index to quantify the relative correlation between a radial mask and the histogram radial line pattern at discrete chromaticity coordinates within a specified search region. The coordinates associated with the strongest radiality index are adopted to represent the effective scene illuminant chromaticity. For a set of controlled test images, the physics-based specular highlight algorithm determined effective scene illuminant chromaticities to a level of accuracy which was nearly three times better than that of a benchmark statistically-based gray-world algorithm. The primary advantage of the specular highlight algorithm was its sustained performance when presented with image conditions of dominant colors, weak specular reflections, and strong interreflections.
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Dedication

I would like to dedicate this thesis to all of my friends and relatives who understood and supported my long hours of commitment to this work. From near or afar, the warmth of your presence in my life helped fuel my drive towards completion!

I would especially like to dedicate this thesis to my father, Carlyle Richard, who has always encouraged his children, Glenn Richard, Judith (Richard) Tantillo and myself, to pursue the higher levels of education which he, himself, did not have the opportunity to pursue. I know that my completion of this degree will make him as proud of me as I am of him.

Finally, I would like to encourage my nephew, Michael Tantillo, and my niece, Laura Tantillo, to continue in their paths towards realizing their pull potentials. I am as proud of who they are as I am of their individual achievements!

WMR
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Chapter 1

Introduction

Mismatches between scene illuminant color and the respective imaging system can result in unwanted color casts in the displayed image. For example, an orange color bias may be observed when viewing photographic prints produced from color film that is balanced for daylight yet exposed under tungsten illumination. Without color correction this bias would be sustained after subsequent digitization of the photographic image.

There are many approaches to ensuring a more faithful color reproduction of an original scene. During image capture, placing an 80A color correction filter (corrects for daylight film exposed under tungsten illumination) over a camera lens would compensate for the illuminant in the example above. In camcorders, good color balance may be achieved by differential gain adjustment of the three color channels based on direct measurement of the average scene color or white point.

Color balancing techniques applied during the image capture stage have the advantage of direct access to illuminant information while it is still available. While these techniques may be effective for a wide variety of scenes, there are conditions where they lose their effectiveness. Further, despite the availability of methods for controlling color balance during image capture, large numbers of images are still produced without deliberate regard
to illumination conditions. Thus, the need exists for effective color correction during the latter stages of the imaging process.

Manual approaches to color correction subsequent to image capture can be very effective but are relatively labor intensive and not practical for high commercial volumes. Many rely on the subjective judgment of equipment operators which may neither be accurate nor consistent. Alternative statistical approaches are available which are more objective, more efficient, and more compatible with higher volumes. For example, algorithms based on the "gray-world" assumption that colors of an average scene integrate to a neutral gray are often employed. While these types of algorithms yield improved color reproduction for most scenes, a competing drawback is that they are ineffective or even counterproductive under certain conditions. For example, a simple gray-world correction of a golf course scene would de-saturate the dominant green colors by overcorrecting towards the magenta.

With the power and speed afforded by today’s digital imaging technologies, opportunities exist for development and utilization of more robust high volume algorithms for color correction. In response to the large numbers of images captured under illumination conditions incompatible with the respective imaging system, such algorithms must be capable of deriving scene illuminant color from information within the recorded image.

Towards this objective there is much research based on a two component reflection model where the illuminant relative spectral power distribution (SPD) is preserved in the specular component. This property is common to inhomogeneous materials regardless of the body
color arising from the counterpart diffuse component. Because inhomogeneous materials of different body colors reflect color mixtures which include a common specular component, and since mixtures of any two colors lie along a straight line in linear chromaticity space, illuminant chromaticity theoretically resides at the convergence of a radial line pattern in the chromaticity histogram. And since a point is uniquely defined by the intersection of two lines, only two objects of different body colors are theoretically required to identify illuminant chromaticity.

On the practical side, illuminant information inherent in the specular highlights of an original scene is corrupted to some degree by the imaging system. This can hinder precise determination of the original scene illuminant chromaticity. However, if the objective is color correction and not an accurate characterization of the original scene illuminant, the illuminant relative spectral power distribution cascaded with scene object reflectivities and the chromatic footprint of the imaging system becomes a useful measure of an effective scene illuminant chromaticity (ESIC). Such a measure can be compared against the white point of the imaging system to derive a color correction that discounts system variables in addition to the initial scene illuminant color.

A primary benefit of utilizing specular highlight algorithms for color correction is the ability to access illuminant information after the image capture stage when direct information is no longer available. However, successful implementation has heretofore been inhibited by image noise and by weak or absent specular highlights. Thus, further refinement is needed to produce a more robust algorithm.
Potential solutions exist in the development of methodologies for uncovering the radial pattern from within the chromaticity histogram and locating the center of convergence. This can be accomplished by first identifying the angular orientations of dominant line signals in the frequency domain, and then assembling those lines about a common point to create a radial mask. The radial mask would then be swept across the histogram to quantify the relative correlation between itself and the radial pattern, for each position, using a *radiality index*. The chromaticity coordinates associated with the highest radiality index would be adopted to represent the ESIC.
Chapter 2

Background

2.1 Color Constancy in Human Vision

Human color vision may be described by way of a simple three component imaging system which consists of an illuminant or light source, a scene containing reflective (or transmissive) objects, and a detection system or, in this case, the human eye (Billmeyer & Saltzman, 1981; Hunt, 1991). Characterized by a spectral power distribution (SPD), the illuminant casts light on the scene where it is modulated in accordance with the spectral reflectances of the objects within (Fairchild, 1994). Some of the reflected light reaches the eye where an image is formed on the long-wavelength-sensitive (L), middle-wavelength-sensitive (M), short-wavelength-sensitive (S) color receptors of the retina.

While the spectral reflectances of most objects can be assumed to be constant, the SPD of light reflected off a given object varies under different illumination conditions. This implies different color *sensations*, yet the human visual system has a remarkable ability to maintain consistent color *perception* of the object (Field, 1988; Wade & Tavris, 1987). For example, while tungsten illumination has a considerably redder content than daylight, a white object is consistently perceived as white when viewed under either illuminant.
Likewise, a red apple is perceived as red and a lime is perceived as green when viewed under either daylight or tungsten. This phenomenon of consistent color perception may be explained by mechanisms of color constancy (Hunt, 1991).

The previous examples describe color constancy as an effect where ambient lighting conditions are discounted such that an object is perceived to be of constant color (Boynton, 1979; Hunt, 1991; Tominaga & Wandell, 1989). In the spatial domain although it is common for relatively large uniform objects to be illuminated across their surfaces by light sources of differing chromaticities, such objects are usually perceived to be of uniform color (Lee & Goodwin, 1994). In the temporal domain the concept of color constancy relates to the ability of the human visual system to “remember” objects as being of constant color from one moment to the next. For example, the colors of a beach ball are perceived to remain constant even as a cloud passes over the sun, changing the illumination characteristics.

Two primary mechanisms can be used to explain color constancy in the human visual system, chromatic adaptation and computational normalization (Fairchild & Lennie, 1992; Lee & Goodwin, 1994). Chromatic adaptation takes from a few seconds up to tens of seconds to stabilize and is associated with the more objective experience of color, sensation. This mechanism involves physiological gain adjustments of the neurons processing color signals. Computational normalization, in turn, is a much faster process than chromatic adaptation and is directly associated with the more subjective experience of color perception. Here, scene elements within the visual field of view are compared against each other to derive perceptual correlates. For example, under different
illuminants the relative redness of an apple as compared to a lime enhances the consistent experience of a red apple.

Various theories offer descriptions of physiological adaptation by the visual system. The von Kries coefficient law explains how sensitivities of the L, M, S (reddish, greenish, bluish) cones are adjusted based on retinal adaptation to white areas of a scene (Wyszecki & Stiles, 1982; Lee & Goodwin, 1994). The retinex theory, in turn, explains how the L, M, S color receptors are used to derive color sensations strongly correlated with object reflectances, the illumination component being discounted (Land, 1964; Land & McCann, 1971). According to the retinex theory, color perception occurs in three stages (Lee & Goodwin, 1994). First, stimuli arising from the L, M, S cones are processed as separate imaging systems to calibrate relative levels of illumination based on maximal response (Land & McCann, 1971). Signals for each receptor type are then normalized to their respective maximum signals to stabilize sensation. Finally, consistent perception is achieved after processing the normalized signals.

2.2 Color Constancy in Machines

Adaptive mechanisms for color constancy inherent in human vision are not indigenous to man-made imaging systems. For example, while an adapted human observer would perceive a "normal" color balance when observing a scene under tungsten illumination, a daylight film would simply record the overabundance of red luminances reflected by objects within. When viewing an uncorrected photograph, the human observer would
then notice an overall red color cast in comparison to the surround (background). Similarly, an uncorrected photograph of a scene captured under fluorescent illumination would exhibit a green color cast. An example of a photograph resulting from a correct match between a daylight film and a (simulated) daylight illuminant is shown in figure 2.1a, while examples of the same scene captured under incompatible tungsten (red cast) and fluorescent (green cast) illuminants are shown in figures 2.1b and 2.1c, respectively.

The combination of an adaptive human visual system with a non-adaptive imaging system offers an explanation of why many unsuspecting amateur photographers are unpleasantly surprised when they view their indoor photographs. For example, a green color cast can be manifested as unflattering skin tones in a wedding scene which is photographed under fluorescent lighting. This underscores the need for mechanisms to ensure color constancy in man-made imaging systems. Following is a discussion of some of these mechanisms.

2.2.1 Controlling Process Variables

Considering the complexity of a photographic color imaging system, there are numerous factors that can affect the quality of color reproduction. Color constancy in photographic prints can be secured by controlling the following conditions from initial image capture through the printing stage (Hunt, 1987):

1) intensity of scene illuminant
2) color of scene illuminant
3) scene subject matter
4) camera lens spectral transmission color
5) lens aperture, exposure time, and film speed
6) film color balance
7) film latent-image keeping properties
8) film processing
9) printer settings
10) paper speed and color balance
11) paper latent-image keeping properties
12) paper processing
13) color and intensity of print illuminant

Although careful monitoring and control of each of these variables can ensure good color balance, doing so requires considerable knowledge and effort. This extreme level of control is incompatible with the majority of photographic interests.

If digitization of film images is a desired alternative to producing photographic prints, the imaging system would be affected by the above variables up to and including film processing. From that point, additional variabilities would arise from the scanner illuminant, detector sensitivities and noise, and from color monitor and color printing system characteristics. Again, considerable technical understanding and effort would be required for successful control of color balance.

2.2.2 Using In-Scene References

A calibration method for achieving acceptable color balance from photographic negatives begins with placement of a neutral test card in the original scene (Hunt, 1987, Stroebel et.
Figure 2.1: Images of fruit scene captured under three different illuminants.
al., 1986). Once the film is exposed, the image of the test card bears the chromatic footprint of the photographic process from the illuminant color up to and including film processing. At the printing stage, a color analyzer is used for tricolor measurements of the projected image of the test card and appropriate exposure adjustments are made. While this is an effective method for color correction, it is inefficient for high volumes. In addition, it is neither practical nor desirable to include a reference card in every scene.

Skintone color can be used as a cue for color correction of images which include human subjects. Manual correction by a capable photo finisher can produce a very pleasing color balance but the results here are highly subjective and the element of human intervention is again not practical for high volumes of photographic production. Automated techniques which monitor skintone for color correction are also available. These methods, however, are subject to the variabilities of skin lightness and tone which limit effectiveness in producing accurate color balance.

2.2.3 Gray-World Algorithms

Without intrinsic scene references, other methodologies must be employed for achieving color constancy in machines after image capture. One family of algorithms relies on the statistically based “gray-world” assumption that colors of an average scene integrate to a neutral gray (Evans, 1951). Accordingly, if the space-averaged scene spectral reflectance is flat, light averaged over the field of view should represent the illuminant relative SPD (D'Zmura & Lennie, 1986). As a practical example involving the photographic printing process, negatives are first evaluated by a tricolor analysis of light which is integrated after transmission through the negative (Current, 1987; Hunt, 1987). Relative color exposures
are then adjusted and controlled by various means to produce color prints which exhibit a near neutral color balance.

Gray-world algorithms yield acceptable color balance for most scenes but they tend to produce less satisfactory results with scene anomalies such as dominant colors (Current, 1987; Lee & Goodwin, 1994). Such scenes violate the primary assumption of a flat space-averaged surface spectral reflectance and a complementary color cast results from overcompensation for the dominant scene color. For example, the omnipresence of green in the image of a golf course would be overcorrected resulting in an overabundance of magenta. An additional shortcoming of gray world algorithms is that most of the light integrated during the tricolor analysis originates from relatively transparent portions of the negative which cause a gray balance bias towards the shadow areas of the original scene (Hunt, 1987). It is possible to train printer operators to recognize and manually correct for atypical images, such as the golf course example above, but human intervention is costly and is relatively inefficient.

2.2.4 Illuminant Determination Using Eigenvectors

Maloney and Wandell (1986) describe a computational method for estimating surface spectral reflectances from sensor responses (quantum catches) when the illuminant SPD is unknown. This method uses weighted basis functions to describe surface spectral reflectances and ambient light. If the illuminant SPD were known, the weights associated with the reflectance basis functions could easily be determined by solving a simple set of simultaneous linear equations. But when the illuminant SPD is unknown, a unique solution exists only if there are fewer surface reflectance basis elements (degrees of
freedom) than numbers of sensors. For a three photoreceptor model (L, M, S cones), this would imply that only two basis elements could be used to describe surface reflectances. This would not be adequate for describing the complex spectral reflectances of many scenes. Further, there is a high correlation between eigenvectors describing reflectances and the basis lights. Thus, they can vary considerably without significant change to the image.

2.2.5 Illuminant Determination During Image Capture

Moving upstream in the imaging process, various algorithms have been designed to take advantage of illuminant information available during the image capture stage. Camcorders utilize gray-world algorithms to estimate the white point of scenes from detector signals; differential adjustments are then made to each of the color channel gains to produce a near neutral color balance. As with the gray-world applications discussed earlier, while this technique is effective for the majority of scenes, overcorrection tends to occur whenever there are dominant scene colors.

Gaboury (1989, 1991) developed a method for discriminating between daylight, tungsten, and fluorescent illuminants based on temporal frequency information. When light is incident on a photodiode, electrical signals are produced with amplitudes that are modulated by the instantaneous intensities of the illuminant. Following, the illuminant is identified by comparing the frequency harmonics against Fourier series of known illuminants. In the case of conventional photography, it is possible to then place appropriate color correction filters in the light path in response to the illuminant
classification. For digital image capture, channel gains can be independently adjusted to achieve a more genuine color balance.

2.2.6 Scene Illuminant Chromaticity from Specular Highlights

As discussed above, color constancy can be achieved by utilizing direct illuminant information which is available during the capture stage of the imaging process. Still, many images are acquired without deliberate regard for the scene illuminant, thus transferring the burden of color constancy to the latter stages when direct illuminant information is no longer available. As discussed earlier, while methodologies used during the latter stages can be effective for a large proportion of scenes, many lose their effectiveness as conditions become less than ideal. Hence, a more robust algorithm is needed. In response to the high volume of images captured under illumination conditions incompatible with the respective image capturing device, such an algorithm must be capable of deriving scene illuminant chromaticity from information within the recorded image. Earlier research points to potential solutions which leverage scene illuminant information contained in specular highlights.

Algorithms which derive scene illuminant chromaticity from specular highlights are based on principles of physics which can be described by a two component reflection model. Also referred to as the dichromatic reflection model (Shafer, 1985) or neutral-surface-reflection model (Lee, Breneman & Schulte, 1986), here, light is reflected from inhomogeneous materials by two independent mechanisms (D’Zmura & Lennie, 1986; Tominaga & Wandell, 1989; Klinker, Shafer, Kanade, 1988; Lee, 1986; Lee, Breneman & Schulte, 1986; Novak & Shafer, 1992) as shown in figure 2.2. One mechanism called
diffuse, body, or subsurface reflection, occurs when light penetrates the air-surface boundary. Below the surface, the light is scattered about where a portion is selectively absorbed by pigments within the material while the remainder is reflected back out of the surface. The ratio of the spectral composition of the light that enters the material to the light that leaves is assumed to be constant for all angles. This mechanism gives rise to the characteristic color of the material and it is diffuse in nature.

![Diagram of incident light, diffuse reflections, pure specular reflection, and pigment material.](image)

*Figure 2.2: Specular and diffuse reflections from an inhomogeneous material.*

The second mechanism is called specular, surface, Fresnel, or interface reflection. Here, light is reflected directly at the air-surface boundary as a function of the refractive index which is essentially equal across the visible wavelengths for inhomogeneous materials (Guenther, 1990; Jenkins & White, 1976; Lee, Breneman & Schulte, 1986). As a result, the relative spectral power distribution of the illuminant is preserved in the specular
component. Specular reflections obey a basic law of physics where the angle of reflection is equal to the angle of incidence about the instantaneous surface normal. Thus, specular reflections are much more directional than diffuse reflections and they exhibit increased directionality with progressively smoother surfaces. It is important to note that surface reflections from homogeneous surfaces (e.g. metals) do not preserve the relative spectral power distributions of the respective illuminants (Lee, 1986; Lee, Breneman & Schulte, 1986; Tominaga & Wandell, 1989). This is due to non-uniformity of the refractive indices across the visible spectrum.

In an experiment by Lee, Breneman & Schulte (1986), eight materials were tested for conformity to the neutral-surface-reflection model. Here, a tele-spectroradiometer was used to measure areas of each object exhibiting different levels of specular reflections under a tungsten illuminant. Data were compared against measurements from a pressed barium sulfate powder (reference white) to derive relative spectral reflectance curves. In their conclusions, Lee et. al. noted that a yellow plastic object, green plant leaf, piece of cloth, painted wood block, and an orange were all well described by the neutral-surface-reflection model, but a ceramic dish and pieces of yellow and blue paper were not.

Tominaga and Wandell (1989) describe a similar experiment where scene illuminants were estimated to an accuracy of a few percent from direct measurements of specular highlights. In this experiment, they verified important assumptions of additivity and separability. Additivity refers to mixtures of two colors forming a color-signal plane in three dimensional color space. All mixtures of the two component colors fall within this plane. Separability, on the other hand, implies that spectral composition of the two
components of reflection are unchanged with viewing angle, i.e. relative spectral power distributions are unaffected by and may be mathematically separated from viewing geometry.

Building upon these concepts, for a given inhomogeneous object, mixtures of the specular and diffuse components form a color-signal plane in three dimensional color space independent of viewing geometries. Similarly, mixtures of reflection components from an object of different color form another distinct plane. Since the common element of the two color-signal planes is the specular component, the planes theoretically intersect along a line or illuminant vector which defines the illuminant chromaticity.

To test this theory, Tominaga and Wandell (1989) alternately placed plastic objects and fruit under tungsten and daylight illuminants. Objects were carefully positioned to minimize interreflections which could act as secondary illuminants. A spectroradiometer was then used to measure the SPD’s from small areas near the specular highlights and within the matte regions. Next, illuminant relative SPD’s were derived by singular-value decomposition (SVD) and results were compared with measurements from a pressed powder of magnesium oxide (MgO) used as a reference white. The conclusions drawn by Tominaga and Wandell (1989) were that the two-component reflection model is adequate for describing color signals to within a few percent without an in-scene reference. The only advanced knowledge was that the object materials were inhomogeneous. It is important to note that this experiment involved direct measurements of scene illuminant SPD’s and did not consider imaging system variables which can disrupt color balance later on in the imaging process.
Consistent with the above findings, D’Zmura & Lennie (1986) describe a physiological model of color constancy in which object hue is derived independent of shape and viewing geometry. In this model, surface reflectances are characterized by one achromatic and two opponent-color channels. Investigations indicated that color constancy was stable with varying object, illuminant, and the observer positions, as well as the illuminant SPD. Graphical representation of this physiological model is similar to that of Tominaga and Wandell (1989) where specular and diffuse components are each represented by a line in three dimensional color space. While different positions along each line represent varying levels of lightness, chromaticity remains constant and all mixtures of the two component colors fall within a distinct chromaticity plane. Two or more planes, each formed by mixtures of the common specular component with different diffuse components, intersect along the illuminant vector.

Extending their model one step further, D’Zmura and Lennie (1986) projected the chromaticity channels down to a single chromaticity plane. Linear combinations of the diffuse and specular components which mapped into a single plane in three-dimensional color space were transformed into a single line which disregarded the lightness component. With this modified representation, illuminant chromaticity was located at the intersection of two lines in a single plane. While this research further reinforced the theories that underpinned the two component reflection model, like the experiments of Tominaga and Wandell (1989), this model was uncorrupted by imaging system variables.
Lee (1986) suggests a method whereby scene illuminant chromaticity can be derived from specular highlights using the two component reflectance model. Consistent with D'Zmura and Lennie (1986), all mixtures of specular and diffuse components map along straight lines in CIE x, y chromaticity space (Judd, 1933) as described by the “Centre of Gravity Law of Colour Mixture” (Hunt, 1991; Wyszecki & Stiles, 1984). Because, in theory, the specular component is common to all inhomogeneous objects within the scene, illuminant chromaticity is located at the intersection of two lines in the chromaticity plane. Lee (1986) further suggests that a multitude of colored surfaces would result in a radial pattern centered about the chromaticity coordinates of the illuminant color. An example of such a radial line pattern is shown in figure 2.3. Note that the illuminant is located at the center of convergence of the radial pattern and not at the center of gravity.

![Figure 2.3: Radial line pattern in CIE x, y chromaticity diagram.](image-url)
Using synthetic images, Lee (1986) first applied a gaussian filter to smooth image noise (Jain, 1989) followed by a Laplacian edge detector to locate color purity changes. Points where color purity changes were at a maximum were called color edge points. Since edge points could arise from material boundaries as well as from strong gradients between body and specular reflections, a method was needed to distinguish between the two. The objective was to preserve data where the gradients arose from specular reflections and reject data where the gradients were caused by material changes.

Towards this objective, numerous pixels on each side of a color edge point, steepest ascent and steepest decent, were plotted on a chromaticity diagram as two subsets which were then tested for co-linearity. If the subsets formed a common line, the data were accepted as representing various levels of saturation of the same color. If the two subsets formed different lines, the gradient was assumed to be due to a material boundary and the data were discarded. Scene illuminant chromaticity was then determined from the image histogram by locating the intersection of the lines which were accepted as representing different levels of saturation of the same color.

While the theories of a two component reflection model were used in the research of Lee (1986), D’Zmura and Lennie (1986), and Tominaga & Wandell (1989), the unique contribution of Lee’s work is the theoretical analysis of scene illuminants after image capture when the original scene illuminant chromaticity has been modulated by the imaging system.
If the ultimate goal is color correction and not an accurate determination of the original scene illuminant chromaticity, the combination of the scene illuminant cascaded with imaging system variables can be operated on as an effective scene illuminant chromaticity (ESIC). Color correction can then discount color distortions induced by the imaging system, in addition to the spectral characteristics of the original scene illuminant. Successful implementation of this type of algorithm may be inhibited by conditions of noise, secondary illuminations due to reflections from nearby surfaces, multiple illuminants, and the absence of strong specular reflections. Accurate determination of the ESIC can be enhanced by applying localized image processing techniques. For example, edge detectors and luminance thresholding can be applied directly to the image to isolate individual objects. Associated object body colors and specular highlights could then be used to determine the ESIC.

Alternatively, image processing techniques can be used to operate on the two-dimensional chromaticity histogram to uncover the radial line pattern. This can be accomplished by first identifying the angular orientations of dominant line signals in the frequency domain and then assembling those lines about a common point to create a radial mask. The radial mask can then be swept across the chromaticity histogram to quantify the relative correlation with the radial pattern for each position using a radiality index. The chromaticity coordinates associated with the highest radiality index can then be adopted to represent the ESIC.

For specular highlight algorithms, an ideal image would consist of a single illuminant, an abundance of uniformly colored inhomogeneous (man-made) objects, no interreflections,
strong specular highlights, and no image noise. In such a scene it would theoretically be a simple matter to uncover the radial pattern and determine the ESIC. To the other extreme, scenes may have multiple illuminants, objects with significant color variation across their surfaces, many interreflections, weak or absent specular highlights and significant noise. By comparison, radial patterns of such images would difficult to uncover. An algorithm was designed to operate on a set of test images with levels of complexity falling between the above two extremes. The specific aspects of design and testing are discussed, below.
Chapter 3

Approach

The primary goal of this research was to develop and test a fundamental algorithm for automated detection of effective scene illuminant chromaticity (ESIC) from specular highlights in digital images. The general approach was to first uncover the radial line patterns buried within the image chromaticity histogram and then to locate the ESIC by finding the geometric center of convergence. Although this concept is relatively simple in theory, the development of an effective algorithm was a complex task primarily due to the plethora of image variables which can alter the radial pattern from its ideal form. Of particular interest, here, were the following: effects of dominant vs. balanced scene color compositions; strong vs. weak interreflections; and strong vs. weak specular highlights. In order to constrain the image variables, scene content was limited to include only single illuminants and man-made inhomogeneous objects of uniform color.

To carry out the investigations, it was necessary to design and assemble a digitally based imaging system, develop algorithms for determining ESIC, design and capture a set of test images, and evaluate algorithm performance. An overview of these activities follows.
3.1 Imaging System Design

Some of the requirements imposed on the imaging system included a means for capturing images under different illuminants, mechanisms for digitizing and storing images, and an environment for manipulating relatively large quantities of data. These requirements were satisfied by using Macbeth light booths for accessing the desired illuminants, daylight film for image capture, Photo CD technology for digitizing film images, PC based version 2.5 of Adobe Photoshop for Windows (Photoshop) for importing images and storing them on a hard disk drive, and a C compiler for algorithm development. Figure 3.1 shows a schematic representation of this imaging system.

Daylight (simulated using filtered tungsten), tungsten (incandescent A) and fluorescent cool white illuminants were selected to represent lighting conditions commonly encountered in conventional photography. In order to characterize these illuminants, a spectroradiometer was used to measure the spectral power distributions (SPD’s) of light reflected from a pressed powder of polytetrafluoroethylene (Halon) reference white placed inside the Macbeth booths. The measured daylight, tungsten, and fluorescent SPD’s are shown graphically in figures 3.2a, b, and c, respectively.

The daylight illuminant SPD is closely matched to the daylight balanced imaging system. Consequently, images captured under this illuminant were expected to produce faithful color renditions of the original scene without significant color correction. The fruit scene pictured earlier in figure 2.1a was captured under daylight illumination and exhibits good color balance without any color correction. In comparison to the daylight SPD, the
Original scene with illuminant. (Macbeth light booths) → Scene captured on daylight film. (Kodak Gold 100ASA) → Image digitized to Photo CD using PIW without Scene Balance Algorithm.

Original scene with illuminant. (Macbeth light booths) → Scene captured on daylight film. (Kodak Gold 100ASA) → Image digitized to Photo CD using PIW without Scene Balance Algorithm.

YCC image acquired into Adobe Photoshop using PC. → YCC image stored in RAW interleaved file format. → YCC image file converted to CIE x, y_{Photo CD} histogram.

Image processing to determine effective scene illuminant chromaticity (ESIC).

Figure 3.1: Schematic diagram of the daylight (D_65) imaging system.
a) daylight illuminant.

![Graph of daylight illuminant]

b) tungsten illuminant.

![Graph of tungsten illuminant]

c) fluorescent illuminant.

![Graph of fluorescent illuminant]

Figure 3.2: Measured illuminant spectral power distributions.
tungsten has a significantly higher red content as evidenced by the monotonically increasing slope from the blue towards the red end of the visible spectrum. This is consistent with the familiar red color cast that can be observed in uncorrected images that have been captured under tungsten illumination as pictured in figure 2.1b. Finally, the measured SPD of the fluorescent cool white illuminant exhibits an overall green bias along with a mercury peak at 546nm. This explains the corresponding green color cast of the uncorrected fluorescent image pictured in figure 2.1c.

After selecting the desired illuminants, scenes were created inside the Macbeth light booths where they were then captured by the daylight imaging system. Kodak Gold 100 ASA daylight balanced color negative film was selected as the capture medium because of its compatibility with the daylight imaging system design. An additional feature of this film is its relatively high spatial resolution which is capable of preserving smaller specular highlight details. The film was exposed using a 35mm single lens reflex camera with a 50mm focal length f/1.8 lens which provided optimum field coverage.

Once exposed, the film was processed by a commercial photographic laboratory using standard processing controls. Consistent with Hunt’s (1987) work in this area, film color balance, film latent-image keeping properties, camera lens spectral transmission, lens aperture, exposure time, film speed, and film processing are all variables which impacted color balance such that original scene chromaticities were lost. However, since the primary interest, here, was the determination of ESIC and not original scene illuminant chromaticity, no unusual efforts were made to control any of these variables.
Following film processing, all of the images were digitized onto Photo CD's in YCC (luminance, chrominance, chrominance) format using a Photo CD Imaging Workstation (PIW). The YCC format is an opponent color space defined in terms of a reference image-capturing device (Kodak Photo CD Products, 1992) where images are encoded as if captured under the standard D<sub>65</sub> illuminant with spectral sensitivities proportional to the CCIR Recommendation 709 reference primary matching functions (CCIR Recommendation 709, 1990). In standard commercial practice, the PIW utilizes film terms to compensate for specific film-type characteristics (e.g. Kodak Gold 100 ASA, version 3) while a Scene Balance Algorithm (SBA) corrects for color casts caused by illuminant departures from the D<sub>65</sub> (Cost, 1993). Because mismatches between the illuminant and the imaging system were of specific interest for this research, the SBA was disabled during digitization. The encoded images were, thus, corrected for film type but not for illuminant SPD’s.

While it can be argued that colors represented by the encoded YCC values would later be distorted by display or printing devices, it can also be argued that these YCC values represent the best estimates of original scene chromaticities once the scenes have been captured and digitized (Photo CD Information Bulletin PCD043, 1993). It is, therefore, suggested that the encoded YCC format is a valid reference color space for deriving ESIC’s. This leads to a functional definition of the image which is “the encoded YCC values as stored on Photo CD”.

After scene capture and image digitization, standard (base) resolution Photo CD images (512 by 768 pixels) were imported to a PC using version 1.0 of the Kodak Photo CD
Acquire (plug-in) Module (Acquire Module) in conjunction with Photoshop. This standard resolution represents the highest of five stored on Photo CD which does not involve any image compression (Kodak Photo CD Products, 1992; Larish, 1993). Combining the software in this way facilitated direct access to 8-bit YCC image data.

Following import to Photoshop, images were written to data files (Greenberg & Greenberg, 1994; Weinmann & Lourekas, 1994) in raw interleaved format, i.e. for each image pixel, YCC code values (0-255) were written to a disk file in three consecutive bytes. In this form, image data were easily accessed by algorithms written in the C programming language.

Having developed the capabilities to capture, store, and access images, an imaging system was in place. Before proceeding with algorithm design, the imaging system was used to capture a preliminary set of images which could be used to test the algorithms during the various stages of development.

3.2 Preliminary Image Set

To support algorithm development, natural (fruit and pepper) scenes were assembled against a black drop cloth inside Macbeth light booths where they were photographed under each of the three illuminants. Included in selected scenes were a Halon (pressed powder of polytetraflouroethylene) reference white and half-matte, half-glossy red and
green tiles. The former provided an in-scene reference white point while the tiles provided well defined specular and diffuse regions for experimentation.

Exposures were bracketed in one f-stop increments during image capture by adjusting shutter speeds to allow fixed aperture stops for consistent depths of focus. After capture, the film was processed and the images were then digitized onto Photo CD’s in YCC format using a PIW. Specific film terms (correction factors applied by the PIW) were used to compensate for the Kodak Gold 100 ASA version 3 film characteristics while the SBA was disabled to preserve the effects of scene illuminant colors.

Following digitization, images were imported to Photoshop using the Acquire Module to access raw YCC data. For each set of bracketed images which contained in-scene references, the Photoshop histogram utility was used to measure 8-bit luminance ($Y_{8\text{-bit}}$) values from isolated areas of the reference whites. Because the image of a 100% diffuse reflector produces a nominal luminance value of 182 (Photo CD Information Bulletin PCD045, 1994), images with white reference luminances measuring closest to that value were selected to represent the “best” exposure among that particular group. Images from bracketed sets which did not include in-scene references were selected based on comparable exposure levels.
3.3 Manual Determination of Effective Scene Illuminant Chromaticity

After sorting the preliminary image set based on measurements of in-scene reference luminances, images of the fruit scenes were used to examine the feasibility of determining ESIC from digital images based on the two component reflection model. For each illuminant, small areas of the specular (glossy) and diffuse (matte) regions of the red and green tiles were isolated using the selection feature in Photoshop. Mean YCC values were then measured from the localized image histograms and recorded. Because illuminant determination from specular highlights is dependent upon a linear color space, YCC data were returned to their original CCIR\textsubscript{709} RGB values using the inverted set of equations shown in Appendix A. Once recovered, specular and diffuse RGB values for both the red and green tiles were further transformed to CIE $x$, $y$ \textsubscript{Photo CD} chromaticity coordinates using the set of equations shown in Appendix B.

It is important to note that original scene CIE $x$, $y$ chromaticities are lost when images are captured on film. However, because CCIR\textsubscript{709} RGB values represent the digital image in a linear color space, equivalent CIE $x$, $y$ \textsubscript{Photo CD} values can be derived which also represent the image. An advantage of operating in CIE $x$, $y$ \textsubscript{Photo CD} chromaticity space is the convenience of directly referencing chromaticity values against information readily available in the literature. Note that the \textquoteleft Photo CD\textquoteright subscript is used to indicate that these values represent the encoded image and not original scene illuminant chromaticities.

After converting YCC data from the colored tiles to CIE $x$, $y$ \textsubscript{Photo CD} coordinates, slopes and intercepts were calculated for each of the two lines adjoining the specular and diffuse
chromaticities. ESIC's were then estimated by calculating the coordinates where the two ("radial") lines intersected. Calculated illuminant chromaticities were then compared to those derived from measurements of the in-scene reference whites. The results shown in figure 3.3 indicate that for each illuminant, chromaticities calculated using the two component reflection model were very close to those measured off the respective in-scene reference whites. In the worst case, daylight, the error was a Euclidean distance of approximately 0.017 which is about 1/5 the distance to the nearest illuminant (fluorescent). These results were accepted as evidence that a non-automated method could be used to estimate ESIC from specular highlights in digital images.

![Figure 3.3: ESIC's calculated from red and green tiles.](image)

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3.4 Algorithm Development

Having successfully demonstrated a non-automated method for determining ESIC from specular highlights in digital images, attention was directed toward the primary goal of developing an automated process. The general approach was to locate the center of convergence (not center of gravity) of the radial or “star” pattern buried within the chromaticity histogram of each image and then locate the ESIC’s by finding the geometric centers of convergence. This process was automated in the form of three distinct C programs, the first of which was designed to calculate the chromaticity histogram from the raw YCC data.

3.4.1 Calculation of the CIE x, y Photo CD Chromaticity Histogram

As discussed earlier, an important factor enabling the use of the two component reflection model for determination of ESIC is the ability to extrapolate lines (representing color mixtures) through a common point in a linear chromaticity space. Accordingly, the first objective was to enable access to the non-linear standard YCC data for subsequent transformation into linear CIE x, y Photo CD chromaticity histograms.

Accessed as unsigned bytes from the raw image files, each triad of YCC values was transformed, first, into CCIR 709 RGB values using the equations shown in Appendix A, and then into CIE x, y Photo CD chromaticity coordinates using the equations shown in Appendix B. Pixel data with Y 8-bit values greater than 235 or less than 20 were discarded to minimize the effects of clipping. After transforming each pixel, the appropriate histogram position within a 64 X 64 array was incremented by one count. Corresponding
to a Euclidean distance of 0.0156 in two-dimensional chromaticity space, this level of resolution (which is approximately 1/5 the distance between the nearest illuminants) was selected to accommodate PC memory requirements and support algorithm speed.

In its simplest form, the CIE \( x, y \) \( \text{Photograph} \) chromaticity histogram was not an effective tool for determining ESIC. This was due to the lack of significant line structure as shown by the histogram in figure 3.4b which was derived from the "pepper" image depicted in figure 3.4a. Instead of the desired line structure, the histogram shows four small cluster regions near the upper portion of spectrum locus. These highly populated chromaticities or "color nodes" arise from the red, yellow, orange, and green body colors which obscure the relatively sparse pixel populations of the specular highlight and transition regions. The spectrum locus shown in the histogram is for reference, only, and is not intended as an accurate representation of saturated colors. The blue, green, and red symbols, interior to the spectrum locus, represent white points measured from the in-scene references for daylight, fluorescent, and tungsten illuminants, respectively. This symbology is consistent for all histograms hereafter.

A heuristic approach was adopted for developing image processing techniques to uncover the radial patterns buried within the histograms. Assuming that the highest concentration of pixels would fall within the body chromaticity regions followed by smaller concentrations in the highlight and transition areas, a \( \log_{10} \) function was applied to pixel counts during calculation of the histogram. The \( \log_{10} \) function was selected as a convenient choice to reduce the dominance of color nodes associated with body
chromaticities while allowing the more modestly populated highlight and transition chromaticities to monotonically emerge. The enhanced histogram is shown in figure 3.4c.

Although the log10 function facilitated overall feature enhancement, the radial line structures were still relatively obscured in the histograms. A technique for further enhancement was developed based on the following hypothesis which is consistent with suggestions by Lee (1990): If luminance levels contributed by the diffuse component of reflection are approximately equal across the surface of a given object, then highly directional specular reflections should significantly increase the overall luminance above the baseline (diffuse) level. Consequently, transitions (radial lines) from diffuse to highlight areas should be characterized, in part, by significant increases in luminance. In contrast, color mixtures that result from interreflections between objects should exhibit a more modest increase in luminance due to the generally diffuse nature of the secondary illuminants.

In keeping with the above hypothesis, a second 64 X 64 array was used to accumulate mean luminances at each discrete chromaticity position during histogram calculation. As shown in figure 3.4d, by weighting the log10 CIE x, y PhotoCD chromaticity pixel counts by the corresponding average luminances, radial line features connecting the specular and diffuse components were enhanced relative to both color nodes and to lines representing interreflections.
Figure 3.4: Radial line enhancement in histograms of "pepper" image.
With a methodology in place for transforming YCC image data into CIE x, y Photo CD histograms with enhanced radial line features, the first of the three C programs was complete. The second C program was developed to calculate the fast Fourier transform (FFT) and the magnitude from the histogram. As will be discussed below, the FFT facilitates automated detection of radial line patterns and the ultimate determination of ESIC.

3.4.2 Calculation of the Histogram Magnitude

An automated method was needed for locating the centers of convergence of the histogram radial line patterns. One method would be to first identify the dominant line signals by scanning the entire histogram at all possible angles and then determine a best-fit point of intersection. An alternative method was developed which simplifies line detection by using the magnitude of the histogram. This method is based on the following rationale.

A continuous line consists of two orthogonal components as shown in the synthetic line image of figure 3.5a. The component along its length is a continuous function while the component across its width is a delta (or spike). Considering these two components, a two-dimensional FFT yields a continuous function from the delta component and a delta from the continuous (Gaskill, 1978). This results in a line in the frequency domain which is orthogonal to its counterpart in the spatial domain. By calculating the magnitude, the phase terms are removed and the orthogonal line passes through the origin as shown in figure 3.5b.
Moving closer to a radial line structure more likely encountered in a chromaticity histogram, a synthetic line segment was created by truncating the original line along its length (rect component) and was expanded in width to form a narrow gaussian component (figure 3.5c). As shown by the corresponding magnitude in figure 3.5d, the longer rect component was transformed into a narrow sinc (note the characteristic "ringing"), and the narrower gaussian component was transformed into a longer gaussian. The result is an elongated magnitude feature which passes through the origin and is orthogonal to its counterpart line segment in the spatial domain.

Building upon the above argument, if the histogram contains multiple lines at different angular orientations, the magnitude should exhibit elongated features which are orthogonal to each of their spatial counterparts and which pass through the origin regardless of line position within the histogram. To verify this claim, the histogram (figure 3.6a) of a real image containing green and blue plastic objects was transformed to secure the magnitude shown in figure 3.6b. As is seen by examination, the histogram contains two radial lines which each extend between the fluorescent (green symbol) illuminant and their respective (green and blue) body chromaticities. Transformation to the magnitude produced two orthogonal features which crossed symmetrically through the origin. The small clusters in the space between the two features were caused by secondary illuminants due to interreflections.
Figure 3.5: Synthetic line images and their corresponding magnitudes.
a) chromaticity histogram of image of green and blue plastic blocks.

b) magnitude of histogram shown in (a).

Figure 3.6: Histogram and magnitude for image of green and blue objects.
In theory, the properties of orthogonality and symmetry through the origin simplify the process of detecting the angular orientations of dominant histogram lines. Peak angles can be detected by a simple rotational scan through a 180 degree arc centered at the origin of the magnitude. This is relatively simple in comparison to scanning the entire histogram at all angles. An additional and equally important advantage of using the magnitude for line detection is the ability to leverage high frequency information. As will be discussed in the next section, high frequency information correlates with narrower (thin line) histogram features.

3.4.3 Automated Detection of Effective Scene Illuminant Chromaticity

Having developed an automated capability for deriving an enhanced CIE x, y Photo CD histogram and for calculating the corresponding magnitude, the first two programs were complete. The remaining third program was developed for automated determination of histogram radial line orientations from the magnitude, assembly of those lines through a common point to form a radial mask, and determination of ESIC by scanning the mask across the histogram to find the position where there is maximum correlation with the radial pattern as measured by a radiality index.

Because strong lines in the chromaticity histogram are transformed into orthogonal features in the magnitude which are symmetric through the origin, histogram line signals, at any angular orientation, can theoretically be detected by evaluating the corresponding magnitude lines, which radiate from the origin, through a range of 180 degrees. Peak angles would then have to be rotated 90 degrees to correspond with their orthogonal
counterparts in the histogram. A polar coordinate system was appropriately adopted to explore the magnitude space.

Radial components were divided into increments equivalent to a Euclidean distance of one pixel along the axes (0.0156) while the angular component was divided into increments of one degree. For each discrete angle, from zero to 179 degrees, the relative line signal was calculated by summing distance weighted magnitude values extending from the origin out to a distance of 32 (edge of the array) in one pixel increments. Because discrete positions defined by the polar coordinate system of the magnitude were not registered with the rectangular coordinate system of the histogram, a bilinear interpolation (Press et al., 1976) method was employed to calculate values for each position. The distance weighting factor was applied to bias responses towards higher frequency components which would tend to correspond with narrower line features.

As relative line signals were calculated using distance weighted sums throughout the entire 180 degree range, results were accumulated in a linear array. A low pass filter kernel five pixels wide (representing five degrees) was then convolved with the array to smooth the relative signal data. This width was derived, empirically, as a tradeoff between reduced signal noise and detectability of line signals. In order to provide continuity, the low-pass kernel was wrapped around the array at the extreme ends of the range. For example, the value at one degree was adopted to represent that of 181 degrees, which fell outside the low-pass window.
After applying the low pass filter, relative signal data were rotated 90 degrees to coincide with the orthogonal lines in the histogram domain. Figure 3.7 shows a plot of relative signal vs. angle derived from the magnitude shown earlier in figure 3.6b. Note the direct angular correspondence between the peak relative line signals and the dominant lines in the histogram.

Figure 3.7: Relative signal vs. angle for histogram in figure 3.6a.

Following the 90 degree rotation of the data, further automation was needed for detecting peak angles from the linear array. The first step was to determine local maxima and minima. At each discrete angle, the relative line signal was compared against those of adjacent angles. For continuity, values at the extreme ends of the range were wrapped around to the other side of the array. If the relative signal at a given angle was greater than those of both neighbors, the angle was designated as a local maximum. Conversely,
if the relative signal was less than those of both neighbors, the angle was designated as a local minimum.

Then, for local maxima which exceeded the nearest local minima, on both sides, by a factor of at least 1.05, the corresponding angle was accepted as being representative of a significant histogram line feature. The threshold level of 1.05 was established, empirically, as a tradeoff between noise reduction and line detectability.

Next, a second-order Laplacian mask (figure 3.8) was convolved non-destructively with the luminance weighted \( \log_{10} \) histogram to create a binary mask (Ballard & Brown, 1982; Baxes, 1984; Gonzales & Wintz, 1987; Jain, 1989). This particular \( 3 \times 3 \) pixel kernel was selected because of its higher sensitivity to brightness changes, compared to gradient operators, and because of its omnidirectional sensitivity to edge features. For traditional applications, the Laplacian operator ideally enhances edges around the perimeters of scene objects. Considering that line features are like the edges of objects which have a zero width in one direction, the convolution with the Laplacian kernel was very effective for isolating histogram radial patterns.

In order to optimize the binary masks, pixels above a threshold level of 0.15 times the maximum value were assigned a mask value of one (for "on") while pixels below were assigned a value of zero (for "off"). The 0.15 threshold level was selected after visual inspection of numerous masks with the ultimate objective of passing desired radial lines while at the same time blocking unwanted features. After thresholding, binary masks were searched for isolated pixels (i.e. pixels without any nearest neighbors), which are then set
to zero. This further reduced unwanted signals by discarding pixels which were not situated on lines. An example of a binary mask for the histogram of the pepper image (figure 3.9a) is shown in figure 3.9b.

\[-1 \quad -1 \quad -1\]
\[-1 \quad 8 \quad -1\]
\[-1 \quad -1 \quad -1\]

Figure 3.8: Laplacian kernel used to create binary masks.

a) histogram of "pepper" image  b) binary mask for "pepper" histogram

Figure 3.9: Histogram and binary mask for "pepper" image.

Assuming that peak angles represent orientations of dominant radial lines, a radial mask was created by assembling those lines through a common point or center of convergence. For the ideal case, the mask should theoretically overlap the histogram radial line pattern.
except for extensions of the each mask line across to the opposite side of the center of convergence. These extensions are artifacts of the algorithm which detects line angles while disregarding line positions. As will be discussed shortly, these line extensions do not adversely impact algorithm performance because they are filtered out by the binary mask.

After creating the binary and radial masks, the radially index was calculated at discrete coordinates within a restricted search region of the histogram (figure 3.10). This index was designed to quantify the relative match between the histogram radial pattern and the radial mask at different positions. The search region was bound between $x_{\text{Photo}}$CD values of 0.24 and 0.43 and $y_{\text{Photo}}$CD values +0.109 (seven pixels) and -0.047 (three pixels) from the daylight locus. This region was designed to include all three illuminants while testing algorithm robustness by providing additional area to allow for false determinations of ESIC.

To calculate the radiality indices at the various positions, the radial mask was swept across the entire histogram search region. Instantaneous chromaticities were defined by the histogram coordinates which coincided with the center of convergence of the radial mask. For each position, the respective radiality index was calculated in the following manner.

Histogram values were first calculated at discrete distances of one pixel along each line of the radial mask using a bilinear interpolation method (Press et al., 1976). If the interpolated value exceeded a threshold level of 0.33, and if the binary mask value was equal to one (for "on"), an associated line index was incremented by one count. The threshold level of 0.33 was selected, empirically, after testing the algorithm on numerous
images. If either the mask value was equal to zero (off) or the histogram value was less than the 0.33 threshold level, the line index was not incremented. In order to minimize the influence of color nodes at prospective ESIC positions, data within two pixels of the radial mask center of convergence were rejected. Owing to uncertainties about precise orientations of radial lines, this process was repeated for all angles within five degrees of the detected (radial mask) angles. The maximum value for each 5 degree range was then adopted for that line and cumulatively summed with the radiality index.

Figure 3.10: Search region of specular highlight algorithm.
Following summation of the maximum signals for each line in the radial mask, the radiality index at that discrete chromaticity location was compared to the highest previous index. If the more recent index was higher, its value was stored for reference along with the associated chromaticity coordinates. Once the entire search region was scanned, the coordinates associated with the highest radiality index were accepted to represent the ESIC.

After determining the ESIC, residual errors were determined by calculating Euclidean distances between the ESIC’s and the reference illuminant chromaticities. To quantify perceptual errors, both the ESIC’s and the reference illuminant CIE x, y \text{Photo} \text{CD} values were first converted to CIELAB using the equations shown in Appendix C. $\Delta E^*_{ab}$ errors were then calculated from the CIELAB values. With the error measurements incorporated, the entire algorithm had been automated in the form of three distinct image processing programs. A summary of the critical image processing steps is presented in Appendix D.

3.5 Testing Algorithm Performance

3.5.1 Design and Capture of Test Images

A set of test images was designed to measure the performance of the specular highlight algorithm in comparison to a simple gray-world under conditions of balanced vs. dominant scene colors, strong vs. weak specular highlights, and strong vs. weak interreflections. In
order to constrain the problem, scene content was restricted to include only single illuminants and man-made objects of uniform color.

Plastic Lego blocks were selected as scene subjects because of their uniform colors and because their flat surfaces which would allow for relatively weak interreflections. “Balanced” color compositions consisted of red (r), yellow (y), green (g) and blue (b) blocks, while scenes with “dominant” colors contained either red-yellow or green-blue combinations.

To create scenes with relatively weak interreflections, plastic blocks were assembled with their surfaces aligned in a common plane. This is, theoretically, an optimum condition for the specular highlight algorithm because it minimizes unwanted histogram line features which could be misinterpreted as specular/diffuse color mixtures (radial lines). For scenes with weak interreflections, strong specular highlights were produced by tilting the blocks to direct lamp reflections towards the camera lens. Care was taken to establish a “reasonable” balance between specular and diffuse reflections which is an optimum condition for producing radial lines. A scene captured with weak interreflections and strong specular highlights is depicted in figure 3.11a and the corresponding magnitude is shown in figure 3.12a.

Similar scenes, but with weak specular highlights, were produced by tilting the plastic blocks so that lamp reflections were directed away from the camera lens. These scenes were designed to test the robustness of the algorithm under less than optimum reflection conditions where the histogram lines would be foreshortened. An example of this scene
a) weak interreflections and strong specular highlights.

b) weak interreflections and weak specular highlights.

c) strong interreflections and strong specular highlights.

Figure 3.11: Images of plastic blocks captured under fluorescent illumination.
a) weak interreflections and strong specular highlights (ref. figure 3.11a).

b) weak interreflections and weak specular highlights (ref. figure 3.11b).

c) strong interreflections and strong specular highlights (ref. figure 3.11c).

Figure 3.12: Histograms of plastic block images.
configuration is shown in figure 3.11b. The corresponding histogram shown in figure 3.12b verifies the shorter radial lines caused by the weak specular highlights.

Other scenes were specifically designed to test the theoretical advantage of the physics based specular highlight algorithm with the statistically based gray-world for evaluating scenes with dominant colors. These scenes were created in a similar fashion to those described above, but with dominant red-yellow and green-blue color combinations.

In order to test the algorithm under sub-optimum conditions of strong interreflections, blocks were then mixed together in pseudo-random piles. Because of the high dimensionality of these scenes, it was not possible to produce strong interreflections with weak specular highlights. An example of a scene with strong interreflections, strong specular highlights, and balanced colors is shown in 3.11c and the corresponding histogram is shown in figure 3.12c. Images such as this were designed to test algorithm effectiveness in discriminating between radial lines and interreflections. Again, similar scenes were captured under the same conditions as above but with dominant red-yellow and green-blue color combinations.

Prescribed test scenes were assembled against a black drop cloth, under Macbeth light booth daylight, tungsten, and fluorescent illuminants, and captured using a 35mm single lens reflex camera with a 50mm f/1.8 lens and Kodak Gold 100 ASA (version 3) daylight balanced color film. To calibrate exposures and ESIC’s, images of Halon reference whites were photographed in one f-stop increments, for each illuminant, at the beginning of each roll of film. Afterwards, the various test scene configurations were assembled inside the
Macbeth light booths. For each combination of illuminant and scene configuration, exposures were bracketed in one f-stop increments by adjusting shutter speeds. This allowed for fixed aperture settings and consistent depths of focus. Once exposed, film was processed by a commercial photographic laboratory an then digitized onto Photo CD’s in YCC format. Consistent with the preliminary image set, film terms were used to compensate for specific film characteristics while the Scene Balance Algorithm was disabled to preserve the effects of the scene illuminants.

Following digitization, images of reference whites were imported to Photoshop using the Acquire Module to access raw YCC data. Best exposures were then determined by selecting the reference white luminances \( (Y_{ref}) \) which were closest to the nominal 182 value. Because test images did not include in-scene reference whites, the “best images” were selected based on exposure levels similar to those of the reference white images.

After image selection, reference ESIC’s were calculated by first returning the reference white YCC data to their original CCIR709 RGB values using the inverted set of equations shown in Appendix A. This was followed by a further transformation to CIE \( x, y \) \( \text{Photo CD} \) chromaticity coordinates using the equations shown in Appendix B. The calculated values shown in table 3.1 were used as reference white points during algorithm testing which is described below.

In order to verify the effectiveness of radial line enhancement, the image shown in figure 3.11c was transformed by each of the three generations of histogram algorithms described earlier. Figure 3.13a shows discrete color nodes in the histogram produced from
straightforward pixel counts by the first algorithm. The modified \( \log_{10} \) transformation of the second algorithm is responsible for the enhanced radial lines and interreflection features shown in the histogram in figure 3.13b. Finally, the luminance weighted \( \log_{10} \) function which was incorporated into the third histogram produced the most pronounced radial line structure amongst the three as shown above in figure 3.13c. The distinct lines which radiate from the illuminant (represented by the green symbol for the fluorescent illuminant under which the scene was captured) demonstrate why the third generation of histogram algorithms was adopted.

Table 3.1: ESIC’s derived from in-scene reference whites.

<table>
<thead>
<tr>
<th>Illuminant</th>
<th>( X_{\text{Photo CD}} )</th>
<th>( Y_{\text{Photo CD}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>daylight</td>
<td>0.2701</td>
<td>0.3044</td>
</tr>
<tr>
<td>tungsten</td>
<td>0.3850</td>
<td>0.3950</td>
</tr>
<tr>
<td>fluorescent</td>
<td>0.3058</td>
<td>0.3667</td>
</tr>
</tbody>
</table>

Histograms of scenes which were captured under daylight and tungsten illuminants without interreflections are shown in figures 3.14a and 3.14b, respectively. Predictably, the daylight radial pattern converges towards the blue (daylight) symbol while the tungsten radial pattern converges towards the red (tungsten).
Figure 3.13: Three generations of histogram transformations.

- a) histogram based on pixel counts
- b) $\log_{10}$ of pixel counts
- c) luminance weighted $\log_{10}$ of pixel counts
Figure 3.14: Histograms of images captured under daylight and tungsten illuminants.
3.5.2 Application of the Algorithm to Test Images

In order to quantify performance, the SHA was applied to each of the 27 test images. For a benchmark comparison, a simple gray-world algorithm was used to derive ESIC by averaging all of the pixel chromaticities in the image. Two error measurements were used to quantify performance for each application of the algorithms. First, Euclidean distances were used to quantify differences between the calculated (using the specular highlight and gray-world algorithms) and reference ESIC’s (measured from the in-scene reference whites) in linear CIE $x$, $y_{\text{Photo CD}}$ chromaticity space. Second, linear chromaticity values were converted to non-linear CIELAB followed by calculation of $\Delta E_{ab}^*$ errors using the equations shown in Appendix C. The $\Delta E_{ab}^*$ values provided a measure of perceptual errors. Test results and data analyses will be discussed in the next chapter.
Chapter 4

Results and Analysis

Test results for the specular highlight and gray-world algorithms are shown in Appendices E and F, respectively. For each of the 27 test images, scene conditions (illuminant type, scene color content, and specular highlight and interreflection conditions) are shown with calculated effective scene illuminant chromaticities (ESIC’s) and primary and secondary error measurements. The primary error metric is a $\Delta$CIE $x$, $y_{\text{Photo CD}}$ Euclidean distance which applies to the linear color space used for the determination of ESIC. $\Delta E^*_{ab}$ is the secondary error metric which is provided, for reference only, to quantify perceptual significance.

Table 4.1 summarizes mean primary and secondary errors for the complete image set using both the specular highlight algorithm (SHA), and the gray-world algorithm (GWA). Figure 4.1 presents linear errors in graphic form. According to these data, mean SHA errors were almost three times smaller than those of the GWA. Critical differences between the two algorithms are apparent when the individual effects of scene color composition, interreflections, and specular highlights are analyzed. These differences will be discussed in the next sections.

58
Table 4.1: Mean errors for the complete image set.

<table>
<thead>
<tr>
<th>Error Metric</th>
<th>Algorithm</th>
<th>Specular Highlight</th>
<th>Gray-World</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Delta \text{CIE } x, y^\text{Photo CD} )</td>
<td></td>
<td>0.0342</td>
<td>0.0950</td>
</tr>
<tr>
<td>( \Delta E^*_{ab} )</td>
<td></td>
<td>18.73</td>
<td>47.60</td>
</tr>
</tbody>
</table>

Figure 4.1: Mean errors for the complete image set.
4.1 Effects of Scene Color Composition

4.1.1 Dominant vs. Balanced Scene Colors

Mean linear and perceptual errors for dominant vs. balanced scene color conditions are presented in numerical form in table 4.2, while linear errors are presented in graphical form in figure 4.2. These errors indicate that the specular highlight algorithm is almost three times more accurate than the gray-world algorithm for determining ESIC’s under each condition. This is primarily because of the geometric basis of the SHA which, in comparison to the GWA, is not directly sensitive to statistical biases.

Even though the SHA determined ESIC’s for scenes with dominant colors to a much higher degree of accuracy than the GWA, it exhibited slightly larger errors for these scenes than for scenes with balanced colors. This is because the “dominant” scene histograms, for this specific set of test images, presented only two radial lines for correlation with the radial masks while the “balanced” scene histograms presented four. The reduced number of features, combined with relatively shallow angles between the histogram radial lines, caused larger correlation errors. These correlation errors, in turn, reduced the overall level accuracy in determining ESIC’s for the scenes with (2) dominant colors.

As mentioned above, the GWA derives ESIC from statistical averages of scene chromaticities. Referring to figure 3.14a shown earlier, three of the radial lines in this
Table 4.2: Mean errors for scenes with dominant vs. balanced colors.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Error Metric</th>
<th>Specular Highlight</th>
<th>Gray-World</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dominant Scene Colors</strong></td>
<td>$\Delta CIE_{x,y}^{Photo,CD}$</td>
<td>0.0389</td>
<td>0.1067</td>
</tr>
<tr>
<td></td>
<td>$\Delta E_{ab}$</td>
<td>22.05</td>
<td>58.88</td>
</tr>
<tr>
<td><strong>Balanced Scene Colors</strong></td>
<td>$\Delta CIE_{x,y}^{Photo,CD}$</td>
<td>0.0246</td>
<td>0.0718</td>
</tr>
<tr>
<td></td>
<td>$\Delta E_{ab}$</td>
<td>12.10</td>
<td>31.03</td>
</tr>
</tbody>
</table>

Figure 4.2: Mean errors for scenes with dominant vs. balanced colors.
“balanced” scene emanate from the daylight (blue symbol) illuminant and extend towards the upper portion of the spectrum locus. Accordingly, one might expect the statistical average (center of gravity) for this scene to be biased in this direction. A simple comparison of the calculated ESIC (for image 2-13 in Appendix F) against the daylight white point (shown in table 3.1) indicates that the gray-world determination does, in fact, fall towards the upper right of the actual illuminant ($\Delta x_{\text{Photo CD}} = +0.040; \Delta y_{\text{Photo CD}} = +0.027$).

The above discussion explains the relatively large errors associated with the GWA when applied to scenes with so-called “balanced” R, Y, G, B color compositions. For the gray-world algorithm, however, a mathematically “balanced” scene is one where the mean chromaticity coincides with the ESIC. This can occur in scenes which contain only neutral colors (e.g. perfect white reflectors), two equally sized objects of chromaticities which fall at equal distances on opposite sides of the ESIC, or any other plurality of object chromaticities where the center of gravity of color mixtures falls at the ESIC.

4.1.2 Red-Yellow vs. Green-Blue Dominant Scene Colors

Table 4.3 shows a breakdown of dominant scene color errors into red-yellow and green-blue combinations; linear errors are shown graphically in figure 4.3. Although the mean SHA errors were almost equal for the two different color combinations, GWA errors were approximately three times larger for red-yellow images than for green-blue. Further, mean red-yellow GWA errors were approximately four times as large as the corresponding SHA errors while the green-blue GWA errors were almost equal to those of the SHA. These differences can be explained by examining the chromaticity histograms.
Table 4.3: Mean errors for dominant red-yellow vs. green-blue color combinations.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Error Metric</th>
<th>Specular Highlight</th>
<th>Gray-World</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dominant Red-Yellow Scene Colors</td>
<td>ΔCIE x, y_{Photo CD}</td>
<td>0.0358</td>
<td>0.1599</td>
</tr>
<tr>
<td></td>
<td>ΔE*ab</td>
<td>20.60</td>
<td>78.74</td>
</tr>
<tr>
<td>Dominant Green-Blue Scene Colors</td>
<td>ΔCIE x, y_{Photo CD}</td>
<td>0.0422</td>
<td>0.0534</td>
</tr>
<tr>
<td></td>
<td>ΔE*_{ab}</td>
<td>23.49</td>
<td>33.03</td>
</tr>
</tbody>
</table>

Figure 4.3: Mean errors for dominant red-yellow vs. green-blue color combinations.
For scenes with dominant green-blue and red-yellow color combinations, the corresponding histograms (figures 4.4a and 4.4b) exhibit distributions where the average chromaticities (centers of gravity) do not coincide with the respective ESIC's. The illustration in figure 4.5 shows the dominant green-blue body chromaticities located at two of the vertices of triangle G I B (where “I” is the illuminant) and the dominant red-yellow body chromaticities located at two of the vertices of triangle R I Y. For a simple scene with equal areas of red and yellow body colors, no interreflections, and no specular highlights, all colors would be represented in the corresponding histogram by chromaticities located at points R and Y. For this scene, the gray-world statistical average would fall exactly between these two points. Following the same logic, a similar claim can be made for the green-blue scene.

Because the midpoint between the red and yellow body chromaticities is located much further from the ESIC than the midpoint between the green and blue chromaticities, the red-yellow gray-world error should be larger than the green-blue. In fact, the relationship between the errors should be proportional to the distances between the midpoints and the respective ESIC’s. This is confirmed by the red-yellow error (0.1772) associated with histogram 4.4b which is more than three times larger than the green-blue error (0.0517) associated with histogram 4.4a. The SHA, on the other hand, is relatively insensitive to these biases in scene color content. Once again, this is because of the geometric basis of the SHA where the ESIC’s are located by finding the centers of convergence of the histogram radial line patterns.
Figure 4.4: Histograms for images with two dominant colors.

Figure 4.5: Gray-world biases for scenes with dominant colors.
4.2 Strong vs. Weak Specular Highlights

The performance of the specular highlight algorithm was essentially unaffected by the scenes with weak specular highlights (table 4.4 and figure 4.6). This can be explained by the presence of adequate histogram line structure (e.g. figure 3.12b) even for the scenes with weak specular reflections. Ironically, gray-world errors were actually smaller for the scenes with strong specular highlights. As illustrated above in figure 4.5, this is because the strong specular reflections produced populations of chromaticities which were closer to the ESIC which, in turn, lured the gray-world averages closer to the true values.

4.3 Strong vs. Weak Interreflections

Finally, the presence of strong interreflections did not significantly impact performance of the SHA (table 4.5 and figure 4.7). This is because of the luminance weighting factor which enhanced the histogram radial line structures while suppressing features associated with interreflections. The gray-world algorithm, by comparison, produced larger errors in the presence of strong interreflections. Because the GWA is statistically based, the interreflections, which acted as secondary illuminants, shifted the mean chromaticities away from the ESIC’s.

As supported by the test results, the primary advantage of the physics-based specular highlight algorithm, compared to the GWA, was its higher level of accuracy when
Table 4.4: Mean errors for strong and weak specular highlights.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Error Metric</th>
<th>Specular Highlight</th>
<th>Gray-World</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strong Specular</td>
<td>$\Delta$CIE $x_\text{\mbox{Photo CD}}$</td>
<td>0.0342</td>
<td>0.0872</td>
</tr>
<tr>
<td>Highlights</td>
<td>$\Delta E^*_{ab}$</td>
<td>18.12</td>
<td>43.66</td>
</tr>
<tr>
<td>Weak Specular</td>
<td>$\Delta$CIE $x_\text{\mbox{Photo CD}}$</td>
<td>0.0342</td>
<td>0.1107</td>
</tr>
<tr>
<td>Highlights</td>
<td>$\Delta E^*_{ab}$</td>
<td>19.96</td>
<td>55.48</td>
</tr>
</tbody>
</table>

Figure 4.6: Mean errors for strong and weak specular highlights.
Table 4.5: Mean errors for strong and weak interreflections.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Specular Highlight</th>
<th>Gray-World</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Error Metric</strong></td>
<td><strong>Mean Error</strong></td>
<td></td>
</tr>
<tr>
<td>Strong Interreflections</td>
<td>( \Delta \text{CIE } x_y )</td>
<td>0.0346 0.1185</td>
</tr>
<tr>
<td></td>
<td>( \Delta E^*_{ab} )</td>
<td>17.40 59.22</td>
</tr>
<tr>
<td>Weak Interreflections</td>
<td>( \Delta \text{CIE } x_y )</td>
<td>0.0340 0.0833</td>
</tr>
<tr>
<td></td>
<td>( \Delta E^*_{ab} )</td>
<td>19.40 41.79</td>
</tr>
</tbody>
</table>

![Graph](image)  

Figure 4.7: Mean errors for strong and weak interreflections.
determining ESIC’s for scenes with dominant colors. Because of the luminance weighting factor, the SHA maintained relatively high levels of accuracy when applied to images with strong interreflections. Finally, for images with relatively weak specular highlights, there was still adequate line structure to support accurate determination of ESIC’s.
Chapter 5

Conclusions and Recommendations

An advanced, automated algorithm has been developed for determining effective scene illuminant chromaticities (scene illuminant plus imaging system variables) from specular highlights in digital images subsequent to image capture. For the prescribed set of controlled test images, the specular highlight algorithm (SHA) determined effective scene illuminant chromaticities (ESIC’s) to a level of accuracy which was nearly three times better than that of the baseline simple gray-world algorithm (GWA). The primary advantage demonstrated by the SHA was its sustained higher level of accuracy when operating on images containing dominant scene colors and/or strong interreflections.

The SHA’s robust performance is attributed to its physics-based approach where ESIC’s are located at the centers of convergence of radial line patterns in a linear chromaticity space. This type of approach is not susceptible to the statistical biases which diminish the performance of simple GWA’s.

Among the enhancement techniques which are used to uncover the histogram radial line patterns, two are critical to SHA performance. The first enhancement is a \( \log_{10} \) function which operates on the linear pixel counts. This non-linear function enhances the more sparsely populated radial line structures relative to (and spanning between) the more
densely populated specular and diffuse chromaticity regions. The second enhancement is a luminance weighting factor which is applied to the log_{10} of the pixel counts for each set of histogram chromaticity coordinates. This further enhances the radial line structures while suppressing features which are associated with interreflections. While it is recommended that future research be directed towards studying the effects of alternative enhancement techniques, it is also recommended that the specific issues of radial line enhancement and interreflection suppression continue to be addressed.

In order to further advance the effectiveness of specular highlight algorithms, more complex scenes should be studied. These scenes should include more subject detail, multiple illuminants, natural objects with non-uniform body colors, and homogeneous objects (e.g. metals). Linear regression techniques would be useful for adjusting threshold levels to optimize algorithm performance under these conditions.

Because of the reduced sensitivities to dominant scene colors and interreflections, the SHA offers potential benefits to commercial photofinishing applications. It is important to recognize, however, that this type of algorithm can become ineffective when operating on scenes which do not contain any specular highlights. By using the SHA in tandem with a GWA, the advantages of each algorithm can be leveraged more favorably. Incorporating parallel image processing techniques, when relatively strong specular highlights are detected in a given image color correction could be heavily biased towards the SHA determination of ESIC. Conversely, for scenes with relatively weak specular highlights color correction could be biased more heavily towards the gray-world determination.
Tradeoffs between speed and performance are usually a large concern during the design of commercial photofinishing equipment. When speed is the primary concern, shorter SHA processing times can be realized by operating on images at reduced resolutions. In order to quantify the performance tradeoffs, however, additional research would be required.

Many machine vision algorithms rely on determinations of ESIC for the removal of specular highlights to recover object shapes and contours. The SHA offers potential benefits, here, in the form of more accurate illuminant determinations. Turning to remote sensing applications, color constancy is often achieved by careful control of imaging system variables or by in-scene cues such as reference panels. For aerial imaging applications where there is adequate resolution for segregating specular from diffuse reflection components, the SHA might offer an alternative approach to color constancy.

In conclusion, an automated algorithm has been developed for determining effective scene illuminant chromaticities from specular highlights in digital images. The primary advantage of this specular highlight algorithm is its sustained high level of performance when applied to images with dominant colors. This sustained performance offers potential benefits to many imaging applications.
References


Appendix A

Equations for Recovering CCIR709 RGB Values from YCC

\[
\text{Luma} = \left(1.402 / 255\right)\text{Luma}_{8\text{-bit}}
\]

\[
\text{Chroma1} = (\text{Chroma1}_{8\text{-bit}} - 156) / 111.40
\]

\[
\text{Chroma2} = (\text{Chroma2}_{8\text{-bit}} - 137) / 135.64
\]

\[
\text{R'} = \text{Luma} + \text{Chroma2}
\]

\[
\text{G'} = \text{Luma} - 0.1942\text{Chroma1} - 0.5094\text{Chroma2}
\]

\[
\text{B'} = \text{Luma} + \text{Chroma1}
\]

For \( R', G', B' > 0.081 \):

\[
\text{R} = \left(\frac{R' + 0.099}{1.099}\right)^{2.22}
\]

\[
\text{G} = \left(\frac{G' + 0.099}{1.099}\right)^{2.22}
\]

\[
\text{B} = \left(\frac{B' + 0.099}{1.099}\right)^{2.22}
\]
Appendix A, continued

For \( R', G', B' < -0.081 \):

\[
R = \left( \frac{R' - 0.099}{-1.099} \right)^{2.22}
\]

\[
G = \left( \frac{G' - 0.099}{-1.099} \right)^{2.22}
\]

\[
B = \left( \frac{B' - 0.099}{-1.099} \right)^{2.22}
\]

For \(-0.081 \leq R', G', B' \leq 0.081\):

\[
R = \frac{R'}{4.5}
\]

\[
G = \frac{G'}{4.5}
\]

\[
B = \frac{B'}{4.5}
\]
Appendix B

Equations for Transforming CCIR\textsubscript{709} RGB to CIE x, y Photo CD

\[
\begin{bmatrix}
X_{\text{PhotoCD}} \\
Y_{\text{PhotoCD}} \\
Z_{\text{PhotoCD}}
\end{bmatrix} =
\begin{bmatrix}
0.4121 & 0.3576 & 0.1802 \\
0.2125 & 0.7153 & 0.0721 \\
0.0193 & 0.1192 & 0.9493
\end{bmatrix}
\begin{bmatrix}
R_{709} \\
G_{709} \\
B_{709}
\end{bmatrix}
\]

\[
X_{\text{PhotoCD}} = \frac{X_{\text{PhotoCD}}}{X_{\text{PhotoCD}} + Y_{\text{PhotoCD}} + Z_{\text{PhotoCD}}}
\]

\[
Y_{\text{PhotoCD}} = \frac{Y_{\text{PhotoCD}}}{X_{\text{PhotoCD}} + Y_{\text{PhotoCD}} + Z_{\text{PhotoCD}}}
\]

\[
Z_{\text{PhotoCD}} = \frac{Z_{\text{PhotoCD}}}{X_{\text{PhotoCD}} + Y_{\text{PhotoCD}} + Z_{\text{PhotoCD}}}
\]
Appendix C

Calculation of CIELAB and $\Delta E_{ab}^*$ from X, Y, Z

Calculation of CIELAB:

$$L^* = 116 \left[ \frac{Y_{\text{illum(derived)}}}{Y_{\text{illum(reference)}}} \right]^{\frac{1}{3}} - 16$$

$$a^* = 500 \left[ \left( \frac{X_{\text{illum(derived)}}}{X_{\text{illum(reference)}}} \right)^{\frac{1}{3}} - \left( \frac{Y_{\text{illum(derived)}}}{Y_{\text{illum(reference)}}} \right)^{\frac{1}{3}} \right]$$

$$b^* = 200 \left[ \left( \frac{Y_{\text{illum(derived)}}}{Y_{\text{illum(reference)}}} \right)^{\frac{1}{3}} - \left( \frac{Z_{\text{illum(derived)}}}{Z_{\text{illum(reference)}}} \right)^{\frac{1}{3}} \right]$$

Calculation of $\Delta E_{ab}^*$:

$$\Delta E_{ab}^* = \left( a^2 + b^2 \right)^{\frac{1}{2}}$$
Appendix D

Image Processing for Automated Detection of ESIC

Calculate CIE x, y Photo CD histogram (64 x 64 pixels -> resolution of 0.0156):

Threshold 20 < 8-bit luminance < 235 to reduce clipping.

Calculate log of numbers of pixels to enhance histogram features.

Weight values by average luminance to further enhance radial lines relative to interreflections.

Fourier transform CIE x, y photo CD histogram to derive magnitude.

Search magnitude to derive angular orientations of dominant lines:

Find relative signals for each line from 0 to 179 in one degree increments.

Use bilinear interpolation to determine values at each position along each line.

Weight each value by distance from origin to bias towards higher frequencies (thin lines).

Apply low-pass filter to smooth relative response vs. angle data.

Select dominant line signals by calculating and thresholding local maxima.

Rotate angles 90 to coincide with orientations of histogram radial lines.

Create binary mask from CIE x, y Photo CD histogram:

Apply non-destructive high-pass filter to histogram.

Threshold to optimize binary mask for "on" and "off" pixels.

Search CIE x, y Photo CD histogram for ESIC:

Assemble radial search mask with dominant lines intersecting at common point.

Calculate radiality index for each position within restricted search region.
Appendix D, continued

- Along each line $\pm 5$ degrees from the nominal radial mask line, calculate line signal by summing the number of "on" pixels which exceed the threshold level. Exclude pixels within $\pm 2$ pixels of search coordinates to minimize dominance by color nodes.
- Select peak line within $\pm 5$ degree range and add to cumulative radiality index.
- Select coordinates with highest radiality index to represent ESIC.

- Calculate CIE $x$, $y$ Photo $CD$ errors.
- Calculate CIELAB values.
- Calculate $\Delta E^*_{ab}$ perceptual errors.
## Appendix E

### Specular Highlight Algorithm - Calculated ESIC’s

<table>
<thead>
<tr>
<th>CD #</th>
<th>Img. #</th>
<th>Source</th>
<th><strong>Spec.</strong></th>
<th><strong>Inter-</strong></th>
<th>Color</th>
<th>Calculated ESIC’s</th>
<th>Delta</th>
<th>Delta</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>refl.</td>
<td>Content</td>
<td>x</td>
<td>y</td>
<td>CIE x, y</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>T</td>
<td>S</td>
<td>W</td>
<td>r, y, g, b</td>
<td>0.3906</td>
<td>0.3805</td>
<td>0.0155</td>
</tr>
<tr>
<td>2</td>
<td>13</td>
<td>D</td>
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** S = strong, W = weak
* D = daylight (0.2701, 0.3044), T = tungsten (0.3850, 0.3950), F = fluorescent (0.3058, 0.3667).

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Appendix F

Gray-World Algorithm - Calculated ESIC's

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** S = strong, W = weak

* D = daylight (0.2701, 0.3044), T = tungsten (0.3850, 0.3950), F = fluorescent (0.3058, 0.3667).

Mean errors: 0.0950 47.60