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**ADVANCEMENTS IN HUMAN SKIN COLOR
CHARACTERIZATION: MECHANISMS,
MEASUREMENT, MODELING, AND APPLICATIONS**

YANG DI

PhD

The Hong Kong Polytechnic University

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The Hong Kong Polytechnic University

Department of Building Environment and Energy Engineering

Advancements in Human Skin Color Characterization:
Mechanisms, Measurement, Modeling, and Applications

YANG Di

A thesis submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy

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Abstract

Human skin color plays a vital role in a wide range of applications, including digital imaging, display calibration, cosmetic product development, and dermatological assessment. However, accurately characterizing and reproducing skin color across diverse illumination and viewing conditions remains a complex challenge due to the interaction of physical properties, visual mechanisms, measurement constraints, and computational modeling limitations. This thesis addresses these challenges through four interrelated studies, each focusing on a different aspect: algorithm development, chromatic adaptation, measurement and modeling analysis, and the integration of experiments and simulations.

The first study developed a color constancy algorithm based on the cone contrast color space, using datasets of real skin reflectance spectra and real light sources to construct reference gamut lookup tables. A loss function was designed to estimate illuminant chromaticities based on multiple gamut features. Experimental results demonstrated that the proposed algorithm consistently outperformed several existing algorithms, especially when image pixels were limited but dominated by skin colors. Furthermore, this study evaluated the influence of camera spectral sensitivity (CSS), revealing that measurement inaccuracies in CSS led to larger errors than those due to variation between similar devices.

The second study examined how the interaction between adapting and stimulus illuminance affects the perceived display white point. Two experiments using full-screen image stimuli were conducted across 44 conditions, including a wide range of illuminance (30 to 15000 lx), CCTs (2500 to 10000 K), a dark condition, and an overcast condition. A lookup table (LUT) mapping adapting illumination to perceived white point CCT was generated. Validation showed that the LUT improved perceived attributes compared to default settings on commercial smartphones. Moreover, images with skin colors showed stronger correlations among comfort, naturalness, and preference, emphasizing the importance of accurate skin color reproduction.

The third study analyzed two main techniques for measuring skin spectral reflectance. While

spectrophotometers offered flexibility, they were affected by aperture size and measurement pressure, whereas spectroradiometers were sensitive to distance. Both methods were limited to fully separate specular and diffuse reflectance, making it difficult to capture accurate facial skin data. This study also reviewed skin modeling approaches, highlighting trade-offs between physical accuracy and computational efficiency. While simplified models reduce complexity by approximating skin layers and chromophores, they may sacrifice accuracy. In contrast, photon-based simulations offer higher fidelity but are computationally intensive.

The fourth study integrated skin scales with skin models to support accurate skin color characterization. Representative skin scales were examined for target population, measurement methods, and color distribution in the CIELAB space. A skin model was constructed using both the Monte Carlo (MC) and Kubelka–Munk (KM) methods. The KM method achieved better performance in matching skin scale values and was used to build a LUT connecting skin color data to reflectance spectra. A psychophysical experiment further investigated the just-noticeable color difference (JNCD) using both patch and face stimuli under D65 and D95 white points. Results indicated that D95 led to less stable chromatic adaptation, with greater variability in ellipse orientation and size. Lighter skin colors consistently showed smaller JNCD ellipses, and patch stimuli yielded more consistent responses than face stimuli.

In conclusion, this thesis presents an investigation into the mechanisms, measurement, modeling, and perceptual evaluation of human skin color. The four studies address challenges across theoretical and applied domains, offering insights and practical tools for enhancing color perception in imaging, display, and skin-related visual technologies. The integration of empirical data, psychophysical experiments, and physically based simulations supports future advances in color science, particularly in contexts where skin color appearance is important.

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Chapter 1 Introduction

1.1 Human visual system

Vision is the primary human sense for interacting with the external environment. It allows us to recognize objects of different colors, navigate spatially, perceive our surroundings, and receive visual information [1]. The human visual system has evolved into a complex network of mechanisms that maintain a stable perception of color appearance despite changes in illumination. The anatomical structure of the eye plays a critical role in shaping visual perception. In many respects, the human eye functions like a camera. The cornea and lens focus incoming light onto the retina at the back of the eye, similar to how a camera lens focuses light onto an image sensor. The retina receives the optical image formed by the eye [1]. The retina is a thin layer of cells, approximately the thickness of tissue paper, located at the back of the eye. It contains photosensitive cells as well as the initial signal for processing and transmission. These photosensitive cells are neurons that are part of the central nervous system, and therefore the retina can be regarded as an extension of the brain. Among the structures of the retina, the fovea plays a central role. The fovea is the region where spatial and color vision are most acute. When observing an object, people naturally move their eyes and head so that the object's image falls on the fovea. For instance, during reading, eye movements ensure that each word projects onto this high-acuity region. The fovea covers approximately 2 degrees in the center of the viewing field.

There are two types of retinal photoreceptors helping us perceive color, as shown in Figure 1-1 [1]. These photoreceptors, known as rods and cones, convert the optical image into chemical and electrical signals that are transmitted to subsequent stages of the visual system. The signals are then processed by a network of neurons before being relayed to the brain via the optic nerve. Rods and cones are named after their general shapes: rods are long and thin, while cones are typically conical in form. However, this naming can be misleading. Foveal cones, which are densely concentrated in the fovea, are also long and thin, making them resemble rods in appearance. The functional differences between rods and cones are more critical than their morphological distinctions. Rods provide vision under low luminance conditions, typically below 1 cd/m^2 , whereas cones function under higher luminance

levels. This transition from rod- driven to cone- driven vision allows the human visual system to operate across a broad range of brightness conditions. At very high luminance levels, such as 100 cd/m^2 , the rods are effectively saturated, leaving cones as the sole contributors to vision. Under intermediate lighting conditions, both rods and cones are active. Vision dominated by rod activity is referred to as scotopic vision; vision mediated by cones alone is termed photopic vision; and vision that involves both rods and cones is classified as mesopic vision. The responses of rods and cones vary according to the energy of incoming light. At low energy levels, only rods respond, as cones do not reach their activation threshold. As energy increases, both types of photoreceptors become active. When the light intensity becomes sufficiently high, rod responses saturate, and only cones continue to function.

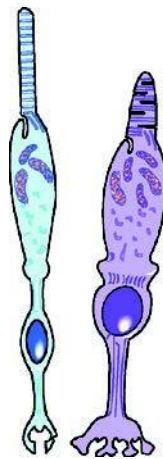


Figure 1-1 Prototypical rod (left) and cone (right) photoreceptors, from [1].

There is just one type of rod receptor that has a peak spectral responsivity at 510 nm. However, the spectral sensitivities of cone photoreceptors differ significantly, as seen in Figure 1-2 [1]. Cones are classified into three types based on their peak responsivity: L (long-wavelength sensitive), M (middle-wavelength sensitive), and S (short-wavelength sensitive) cones. As shown in Figure 1-2, the spectral sensitivities of the three cone types are highly overlapping, enabling color vision. The rod system is incapable of color vision since there is only one type of rod. This can be demonstrated by observing a typically colorful scene under very low light levels, where color perception diminishes.

Nevertheless, understanding the anatomical structure of the human eye alone is insufficient to fully explain visual perception. To address this, scientists have proposed several theoretical models of the

human visual system. Two major theories have been developed to explain color vision: the trichromatic theory and the opponent color theory.

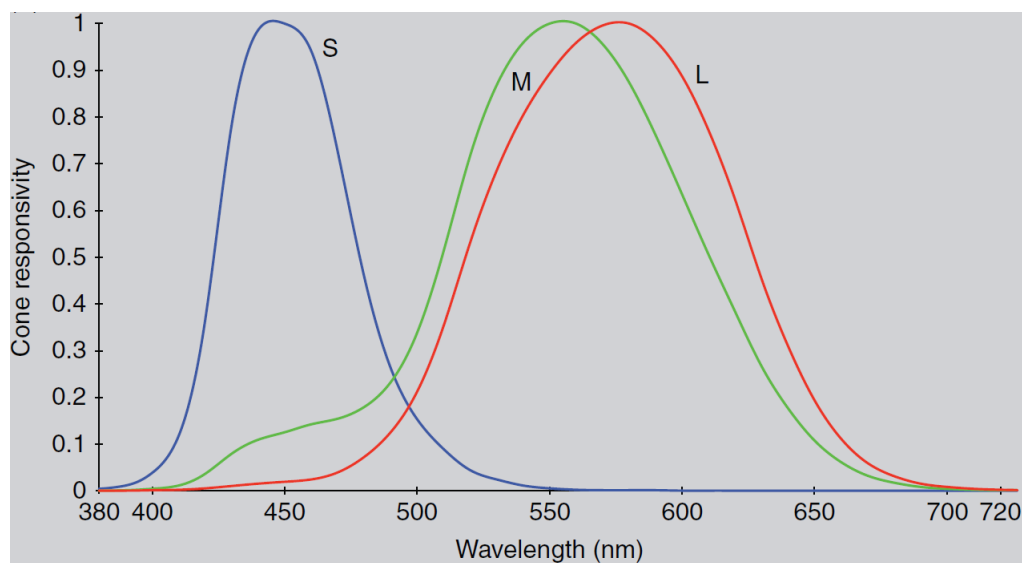


Figure 1-2 Spectral responsivities of L, M, and S cones, from [1].

The trichromatic theory, based on the work of Young and Helmholtz [2], was developed in the latter part of the 19th century. This theory proposes that there are three types of photoreceptors, each sensitive to a specific portion of the visible spectrum: long wavelengths (red), medium wavelengths (green), and short wavelengths (blue). The trichromatic theory suggests that color perception arises from the combined activity of these three receptors. While the trichromatic nature of cone photoreceptors is now well established, the assumption that the brain directly receives information from the three receptor types does not fully account for certain visual phenomena. Then, Hering proposed the opponent color theory [3], which challenged the trichromatic theory. He observed that certain color combinations, such as reddish-green or yellowish-blue, are not perceived, while others, such as red and yellow or green and blue, are commonly experienced. Based on these observations, Hering hypothesized the existence of three opponent pairs: light versus dark, red versus green, and yellow versus blue. These two theories were later found to describe different stages of color vision. This understanding was supported by the research of Hurvich and Jameson [4]. In the first stage, the photoreceptors function trichromatically. In the second stage, however, retinal neurons recombine the signals into opponent channels. This transformation from LMS signals into opponent channels serves to decorrelate the color information, thereby enhancing transmission efficiency and reducing noise.

In addition to the physiological mechanisms of color vision, cognitive visual mechanisms also influence the perceived color appearance. One such mechanism is color constancy, which plays an important role in this study. Color constancy refers to the perceptual phenomenon whereby the perceived color of a surface remains relatively stable despite changes in the illumination's color and luminance. This phenomenon is supported by mechanisms such as chromatic adaptation and memory color. However, color constancy is not perfect and can be weak when observed carefully. For example, a piece of white paper tends to appear white under tungsten, fluorescent, or daylight illumination. The study of color appearance, chromatic adaptation, and the development of color appearance models contributes to a more comprehensive understanding of the human visual system.

1.2 Chromatic adaptation

Chromatic adaptation is widely regarded as the most fundamental first-order phenomenon of color appearance. Adaptation is the ability of an organism to adjust its sensitivity to a stimulus in response to changes in stimulation circumstances. Chromatic adaptation specifically describes the ability of the human visual system to maintain the perceived color of objects under varying illuminants. In the absence of chromatic adaptation, perceived colors would resemble those captured by digital cameras without white balance correction. For example, a photograph of a white sheet of paper taken under incandescent light typically appears yellowish. This occurs because cameras lack the human visual system's ability to adjust their relative responsiveness of red, green, and blue as the human visual system adjusts the response of visual mechanisms. Three types of adaptation are particularly essential in color vision: dark adaptation, light adaptation, and chromatic adaptation.

Dark adaptation and light adaptation are often confused due to their functional similarities. Dark adaptation occurs when the visual system increases its sensitivity in response to reduced illumination. For instance, when a person enters a darkened room from a bright outdoor environment, the room initially appears completely black. However, after several minutes, objects within the room gradually become visible. This transition results from the visual system adapting to the low-light environment. Initially, cone cells increase their sensitivity, reaching a relatively stable state within a few minutes. Around ten minutes after entering the dark environment, rod cells begin to dominate visual sensitivity.

Under the influence of rod cells, visual sensitivity continues to increase until it stabilizes after approximately 30 minutes. Light adaptation, by contrast, is essentially the reverse of dark adaptation. This process occurs, for example, when one exits a dark room into bright sunlight. Similarly, while stars are clearly visible in a dark night sky, they become invisible during the day because daylight illumination is several orders of magnitude higher, and the human eye becomes less sensitive to such faint light sources. In light adaptation, the visual system must reduce its sensitivity to avoid being overwhelmed by excessive light. The time course of light adaptation is much shorter, approximately 5 minutes, compared to 30 minutes for dark adaptation.

Chromatic adaptation is closely related to dark and light adaptation and has a similar physiological basis. Chromatic adaptation can be readily observed by viewing a white sheet of paper under different types of illumination, such as daylight, fluorescent light, and incandescent light. Although these three light sources have markedly different spectral characteristics, the paper typically continues to appear white. This perceptual constancy suggests that the visual system compensates for the spectral characteristics of the illuminant. Chromatic adaptation is often regarded as a sensory mechanism that responds automatically to stimulus changes. However, studies have indicated that the mechanism of chromatic adaptation depends on the understanding of objects and their lighting environment [5]. Thus, chromatic adaptation consists of two mechanisms: sensory and cognitive mechanisms. The sensory mechanism includes automatic responses such as retinal gain control, where retinal neurons adjust their gain and response time to adapt to changes in the environment [6]. In contrast, the cognitive mechanism is based on knowledge and expectations about the scene and the illumination. It enables the visual system to infer the color of an object by considering contextual information, such as the nature of the illuminant and the perceived identity of the object. This distinction is important for understanding how chromatic adaptation operates in natural viewing conditions.

Another critical feature of chromatic adaptation is its time course, which plays a significant role in color science research. Understanding the time course of chromatic adaptation is crucial for designing psychophysical experiments and assessing the extent of adaptation. Several studies [7-8] have investigated the chromatic adaptation time course of color appearance judgment in detail. For instance, Fairchild and Reniff [8] conducted a psychophysical experiment in 1995 using a computer-controlled

CRT display at a constant luminance level. Three observers tracked color appearance over a two-minute transition between different chromaticities. The results indicated that approximately 90% of the chromatic adaptation was completed within 60 seconds under constant luminance conditions. It is important to note that when chromatic changes are accompanied by substantial changes in luminance, the chromatic adaptation process becomes slower [9].

Several chromatic adaptation models have been developed to simulate cone responses or their simplified combinations. In the application of CIE colorimetry, the CIE tristimulus values XYZ are often transformed into cone responses such as LMS. A linear transformation is typically used to convert between XYZ and LMS, facilitating chromatic adaptation processing. Extensive research has focused on optimizing chromatic adaptation transformations. Calabria and Fairchild [10] conducted a comprehensive comparison of various proposed linear chromatic adaptation transformations. Their study demonstrated that, for most practical applications, images processed using different optimized transformation matrices were visually indistinguishable. The only transformation that produced noticeably different results was the one based directly on cone responsivities. This finding confirmed that using optimized transformation matrices, rather than relying on unmodified cone responsivities, offers perceptual advantages, which aligns with the evaluations conducted by CIE Technical Committee 8-01 [11]. As a result of these efforts, the CIE Technical Committee 8-01 recommended a linear chromatic adaptation transformation known as CAT02 for use in color management applications [11]. The CAT02 model has been widely adopted for its balance of simplicity, computational efficiency, and perceptual robustness.

1.3 Color appearance models

Chromatic adaptation is the most fundamental and essential component among color appearance phenomena, and accordingly, it forms the core of all color appearance models through a chromatic adaptation transform (CAT) that aims to simulate this visual process. However, chromatic adaptation transforms alone are limited. While they can predict color matches across different viewing conditions, CATs do not provide direct measures of perceptual attributes such as hue, chroma, or brightness. Therefore, comprehensive color appearance models (CAMs) are required to describe and predict how

color stimuli appear under a wide range of viewing conditions.

A color appearance model should predict a range of perceptual attributes. These include absolute appearance attributes such as brightness, colorfulness, and hue, as well as relative appearance attributes such as lightness, chroma, saturation, and hue. At a minimum, a CAM should reliably predict lightness, chroma, and hue. More advanced models incorporate brightness and colorfulness, and account for luminance-dependent effects such as the Stevens effect and the Hunt effect.

A typical color appearance model consists of three major components [12]. The first is a chromatic adaptation transform such as CAT02. The second is a dynamic response function that combines the post-adaptation signals. The third is a uniform color space for representing appearance attributes such as brightness, lightness, colorfulness, chroma, and hue.

The CIE 1976 $L^*a^*b^*$ color space (CIELAB) is a simple yet widely adopted color appearance model that generally follows the construction described above. Originally developed as a color space for the specification and quantification of color differences, CIELAB defines color difference as the Euclidean distance between two points within its three-dimensional space. In 1994, the CIE recommended an improved color difference formula based on CIELAB [13], which was later refined into the CIEDE2000 formula [14]. Both were designed to provide more accurate perceptual correlates of color difference. In developing these formulas, the CIE effectively constructed a color space that included basic predictors of perceptual attributes.

The construction of CIELAB begins with two sets of CIE XYZ values: those of the stimulus (X, Y, Z) and those of the reference white point (X_n, Y_n, Z_n). A chromatic adaptation process is implicitly applied by normalizing the stimulus tristimulus values relative to the reference white, using the ratios X/X_n , Y/Y_n , and Z/Z_n . Next, a nonlinear compression is applied to the normalized tristimulus values using a cube root function. This nonlinearity models the compressive relationship between physical stimulus intensity and perceptual response [15]. The resulting signals are then combined into three dimensions corresponding to lightness L^* , the red–green axis a^* , and the yellow–blue axis b^* . Finally, scaling constants are applied to ensure approximately uniform perceptual spacing and to maintain correct relationships among the three dimensions.

The CIELAB equations are given in Equations (1-1) to (1-4).

$$L^* = 116f\left(\frac{Y}{Y_n}\right) - 16 \quad (1-1)$$

$$a^* = 500\left[f\left(\frac{X}{X_n}\right) - f\left(\frac{Y}{Y_n}\right)\right] \quad (1-2)$$

$$b^* = 200\left[f\left(\frac{Y}{Y_n}\right) - f\left(\frac{Z}{Z_n}\right)\right] \quad (1-3)$$

$$f(\omega) = \begin{cases} (\omega)^{\frac{1}{3}} & \omega > 0.008856 \\ 7.787(\omega) + 16/116 & \omega \leq 0.008856 \end{cases} \quad (1-4)$$

The L^* value defined in Equation (1-1) is perceived lightness, with a range from 0.0 for black to 100.0 for a diffuse white. In some cases, such as in the presence of specular highlights within images, L^* values may exceed 100.0. The a^* and b^* dimensions correspond approximately to perceptual red versus green and yellow versus blue chromatic content, respectively. Both a^* and b^* can take on positive or negative values, with a value of 0.0 indicating an achromatic stimulus such as white, gray, or black. In addition, the CIELAB model also includes two derived correlates to further describe color attributes: chroma C_{ab}^* and hue angle h_{ab} , as defined in Equations (1-5) and (1-6).

$$C_{ab}^* = \sqrt{a^{*2} + b^{*2}} \quad (1-5)$$

$$h_{ab} = \tan^{-1}\left(\frac{b^*}{a^*}\right) \quad (1-6)$$

Chroma C_{ab}^* shares the same units as a^* and b^* . For achromatic stimuli, such as white, gray, or black, C_{ab}^* is 0.0. The hue angle h_{ab} is expressed in positive degrees, measured from 0° on the positive a^* axis and increasing counterclockwise. The CIELAB model takes the XYZ tristimulus values of both the stimulus and the reference white as input, and outputs estimates of lightness, chroma, and hue.

While the CIELAB space serves as a simple example of a color appearance model, it exhibits several known limitations. Its perceptual uniformity can be evaluated by comparing constant hue and chroma contours derived from the Munsell Book of Color. In CIELAB plots, constant chroma contours are represented as concentric circles, while constant hue contours appear as straight lines radiating from the center. Since the Munsell system is designed to be perceptually uniform in hue and chroma,

CIELAB provides a reasonably good representation of this uniformity. However, further examination using CRT displays capable of reproducing higher chroma levels than those typically available in the Munsell Book has revealed discrepancies between observed and predicted contours, particularly in red and blue regions [15]. Beyond chromatic adaptation, CIELAB also exhibits limitations in hue prediction accuracy, prompting the development of more advanced appearance models. Moreover, CIELAB lacks mechanisms to account for several key perceptual effects. It includes no dependency on luminance level, rendering it incapable of predicting luminance-dependent phenomena such as the Hunt and Stevens effects. It also lacks sensitivity to background and surround conditions, and therefore cannot predict simultaneous contrast, such as changes in image contrast due to variations in surround luminance. Finally, CIELAB does not provide correlates for absolute appearance attributes such as brightness and colorfulness. These shortcomings suggest that it is both necessary and feasible to improve upon CIELAB in the development of more comprehensive color appearance models. Nonetheless, CIELAB remains a simple and practical tool that can serve as a benchmark for evaluating the performance of more sophisticated models.

Through ongoing refinement and optimization by researchers, numerous color appearance models have been developed, including the RLAB model [16] and CIECAM97s [12]. In 2002, the CIE introduced CIECAM02 [11], which represented the most advanced model available at the time, making a balance between complexity and functionality. Equations describing perceptual attribute correlates are essential components of any color appearance model. While CIELAB provides basic equations for predicting lightness, chroma, and hue, CIECAM02 expands upon this foundation by incorporating additional formulae to estimate brightness, saturation, and colorfulness. This allows the model to predict a more comprehensive set of color appearance attributes across a broad range of viewing conditions.

In applying CIECAM02, several terms related to the visual field must be clearly defined. The size of the stimulus is typically specified as a 2° field at the center of view. The background is defined as the approximately 10° area immediately surrounding the stimulus, and the adapting field encompasses the remainder of the visual field outside the stimulus area. The input data required for CIECAM02 include the relative tristimulus values of the test stimulus (X, Y, Z), the tristimulus values of the reference

white (X_W, Y_W, Z_W), the adapting luminance L_A in cd/m^2 (often estimated as 20% of the luminance of a white object in the scene), the type of surround (categorized as dark, dim, or average), and a determination of whether discounting-the-illuminant is to be applied. Surround conditions are typically assigned based on the viewing medium: average surrounds for reflective prints, dim surrounds for emissive displays such as CRTs and televisions, and dark surrounds for projected transparencies. However, the surround is not strictly linked to the medium; for instance, it is entirely possible for reflective prints to be viewed in a dark surround or for transparencies to be evaluated under an average surround. One of the key advancements in CIECAM02 is the incorporation of a linear chromatic adaptation transform, known as CAT02. The transformation begins by converting CIE tristimulus values into RGB responses using the optimized CAT02 transformation matrix, as described in Equations (1-7) and (1-8). This transformation must also be applied to the tristimulus values of the adapting stimulus to ensure consistency in the chromatic adaptation process.

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = M_{CAT02} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} \quad (1-7)$$

$$M_{CAT02} = \begin{bmatrix} 0.7328 & 0.4296 & -0.1624 \\ -0.7036 & 1.6975 & 0.0061 \\ 0.0030 & 0.0136 & 0.9834 \end{bmatrix} \quad (1-8)$$

The matrix M_{CAT02} is normalized such that the tristimulus values corresponding to an equal-energy illuminant ($X = Y = Z = 100$) yield equal cone responses, i.e., $L = M = S = 100$. The degree of chromatic adaptation is represented by the D factor, which is calculated as a function of the adapting luminance L_A and the surround parameter F , as specified in Equation (1-9). Theoretically, D ranges from 1, indicating complete chromatic adaptation, to 0, representing no adaptation. In practical applications, however, the value of D seldom falls below 0.6, reflecting the typical extent of human visual adaptation in most viewing environments.

$$D = F \left[1 - \left(\frac{1}{3.6} \right) e^{-(L_A + 42)/92} \right] \quad (1-9)$$

The introduction of the parameters D has enhanced the efficiency and accuracy of CIECAM02 relative to earlier color appearance models.

1.4 Outline

The thesis is structured as follows.

Chapter 2 provides a comprehensive literature review, covering key areas such as color constancy, chromatic adaptation, and skin color characterization. It examines existing research and methodologies, identifying significant gaps in the current understanding.

Chapter 3 outlines the research gaps identified from the literature and presents the key research questions that drive the study.

Chapter 4 proposes a color constancy algorithm based on skin color, aiming to improve chromaticity estimations of illuminants in images, particularly for skin-dominant images.

Chapter 5 investigates how the interaction between adapting and stimulus illuminance affects the perceived display white point, conducting two experiments to examine how these factors jointly influence chromatic adaptation and the visual perception of white points.

Chapter 6 focuses on the characterization of human skin color by examining measurement techniques, modeling strategies, and the challenges in accurately capturing skin appearance, with particular emphasis on the biophysical structure and optical properties of skin.

Chapter 7 analyzes existing skin scales, develops a biophysical skin model and LUT for skin color characterization, and validates them through psychophysical experiments on skin color discrimination under different viewing conditions.

Finally, Chapter 8 provides a conclusion, summarizing the key findings of the thesis.

Chapter 2 Literature review

2.1 Color constancy algorithm

The study of color constancy contributes to understanding how the human visual system maintains consistent color perception and the limitations that prevent perfect constancy in real-world scenes. Research in this field also suggests that computational color constancy has important applications in machine vision. Most existing algorithms are designed for images captured by conventional digital cameras and can be categorized into three main types: statistical, gamut-based, and learning-based methods [17].

Among statistical methods, the well-known *gray world* algorithm [18] assumes that the average color of an image is gray. This algorithm provides a reliable estimation of illuminant chromaticities when the color distribution of the image is diverse and abundant. However, it may fail when the image is dominated by a large monochromatic color, such as the skin color in selfies. Another commonly used method, the *max-RGB* or *white patch* algorithm [19], assumes that the maximum responses in each channel approximate a white reference. However, its reliability will significantly reduce when there is a lack of specular highlights in the image to be processed. The *shade of gray* algorithm [20] is similar to the above two algorithms. The *gray world* and *white patch* algorithms are based on average chromaticity and the brightest reflectance of a scene, which are two extreme instantiations of the Minkowski norm. Instead of computing the average or maximum value, the *shade of gray* algorithm calculates the Minkowski p -norm of all pixels to estimate scene-illuminant chromaticities. However, the effectiveness of this method is also based on the chromaticities of pixels and will become unreliable when pixels are cropped. In addition, digital cameras may capture exceptional scenes, such as large regions of sky or lawn, which can easily invalidate the above algorithms. This issue is further exacerbated in front cameras, which typically capture smaller scenes with less content. As a result, these cameras are more susceptible to inaccurate white balance corrections, especially when the algorithms rely heavily on the chromaticities of pixels.

Some color constancy algorithms hypothesize that skin colors provide enough reliable information to estimate the scene illuminant [21-22]. Human skin color is special for the human visual system since

the human face can be recognized and filled with the appropriate skin color by the memory color mechanism [1], even under the chromatic illuminant. Skin color is also a particular object for color constancy algorithms. It is ubiquitous in photographic images and portraits and tends to form a cluster in the color space [23]. Bianco and Schettini [21] proposed a color constancy algorithm that processes human skin color data in RGB color space to estimate the scene-illuminant chromaticities. However, the RGB color space encodes device-dependent signals and does not fundamentally represent the biological properties of the human visual system. In contrast, the cone contrast color space is naturally designed to describe cone signals produced by human eyes [24], possibly providing more physiological information than RGB and RGB-based color spaces for white balance correction. Crichton et al. [24] investigated the utility of skin color represented in cone contrast space for illumination estimation. They demonstrated that the gamut of human skin in the physiological color space [25] has distinctive features that can be effectively used to differentiate between similar illuminations. However, their reference gamuts were limited in generalizability, as they were constructed using only a few illuminants generated by a single LED illuminator and a small set of hand skin reflectance spectra.

2.2 Chromatic adaptation

Chromatic adaptation, the visual system's ability to adjust to changes in illumination and maintain consistent color perception, is influenced by a variety of environmental factors. Over the past decades, a substantial body of research has sought to quantify how the degree of chromatic adaptation varies under different adapting conditions, particularly in terms of adapting chromaticity, luminance, viewing mode, viewing medium, and field of size.

One of the most widely examined factors is the adapting chromaticity. Smet et al. [26] systematically studied a diverse set of adapting CCTs (including 2000, 2856, 4000, 5500, 6500, 12000 K, and an adapting CCT at infinite K) as well as chromatic adapting lights (red, yellow, green, blue, and magenta). They concluded that the degree of chromatic adaptation generally decreased as the adapting chromaticities became more extreme. Li et al. [27] confirmed this finding by experiments with adapting CCTs from 1500 to 15000 K and D_{uv} ranging from -0.03 to $+0.03$, under fixed adapting luminance, highlighting the significant impact of chromaticity on chromatic adaptation.

Similarly, Huang and Wei [28] observed incomplete adaptation under low-CCT conditions even when the ambient luminance was extremely high (up to 3000 cd/m^2), indicating that high luminance alone does not guarantee complete chromatic adaptation. The influence of both adapting chromaticity and the viewing medium has also been examined. Zhai and Luo [29] compared surface-reflective and self-luminous medium under a broad range of adapting CCTs (from 3100 to 16000 K), finding that surface stimuli produced higher degrees of adaptation than self-luminous displays.

Although the effect of viewing mode has been extensively studied, its interaction with other factors often remains ambiguous. Studies by Yamauchi et al. [30], Shinoda et al. [31], and Olkkonen et al. [32] explored the effect of viewing mode on chromatic adaptation, often using CRT monitors or real surfaces. However, these studies generally confounded viewing mode and viewing medium, making it difficult to isolate the individual effect. Ayama et al. [33] employed both monitors and printed charts in the experiment, but did not compare the effects of the viewing mode and medium.

Wei and Chen [34] proposed that viewing mode, not viewing medium, more strongly affects chromatic adaptation. By changing stimulus and ambient luminance to shift the viewing mode, they found that adaptation was more strongly influenced by luminance contrast, particularly at low CCTs. Another important factor is the adapting field size. Hanselaer et al. [35] reported that larger adapting fields result in greater chromatic adaptation compared to smaller fields.

Overall, these studies collectively demonstrate that chromatic adaptation is not solely determined by adapting luminance or chromaticity but emerges from a complex interaction among multiple perceptual and environmental variables. However, most existing studies have not examined the joint effects of adapting and stimulus illuminance on chromatic adaptation, nor have they investigated the specific influence of stimulus illuminance when observers view complex image-based stimuli. As a result, the understanding of how adapting and stimulus illuminance interact to shape perceptual white point remains limited, especially under realistic display scenarios.

2.3 Human skin color

2.3.1 Skin structure

The color appearance of human skin is influenced by many factors, including its layered structure and the optical properties of its molecular components, such as fibers and cells. These molecular components interact with light in complex patterns, producing the distinctive visual characteristics of skin. As an inhomogeneous medium and the interface between the body and the external environment, skin conveys rich information about an individual's background, health status, lifestyle, and physiological condition [36]. Human skin consists of three primary layers: epidermis, dermis, and hypodermis [37], as illustrated in Figure 2-1. Each layer of the human skin contains distinct biological components and varies in thickness, contributing to the overall optical behavior and appearance of the skin.

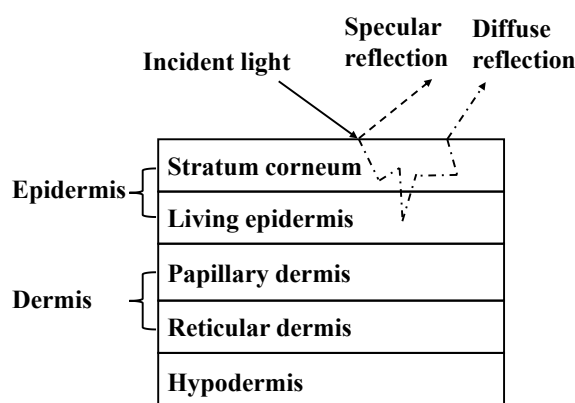


Figure 2-1 Structure of the human skin.

The epidermis is the outermost and thinnest of the three skin layers, measuring approximately $100\ \mu\text{m}$ in thickness [38]. This layer lacks blood vessels and is primarily composed of keratinocytes [39], which form a protective barrier against environmental damage. These keratinocytes are continuously renewed as outer cells are shed and replaced by new ones, forming the stratum corneum, which is the most superficial sublayer of the epidermis [40]. Beneath the stratum corneum lies the living epidermis, which contains additional cell types that influence the color appearance of the skin, including melanosomes responsible for melanin synthesis. Melanin, a key chromophore contributing to skin color, exists in two forms: pheomelanin and eumelanin, which differ slightly in their absorption

characteristics. [41].

The dermis lies beneath the epidermis and is considerably thicker than the epidermis, with a typical thickness of approximately 1 to 4 mm [38]. Structurally, the dermis comprises two sublayers, a superficial sublayer adjacent to the epidermis called the papillary dermis and a deeper and thicker sublayer called the reticular dermis. The dermis contains a significant number of blood vessels. Hemoglobin, beta-carotene, bilirubin, and water are the primary absorbing substances in the dermis within the visible wavelength range. Hemoglobin exists in both oxygenated (oxyhemoglobin) and deoxygenated (deoxyhemoglobin) forms, and it contributes to the reddish appearance of human skin [36].

The hypodermis, or subcutaneous tissue, is a layer mainly composed of adipocytes and lies beneath the dermis. Its thickness varies across individuals and body regions, ranging from 1 to 6 mm [38]. The primary function of the hypodermis is to store energy and regulate temperature.

2.3.2 Optical properties

When an incident light reaches the skin surface, it undergoes absorption, scattering, reflection, and refraction. A portion of the light is directly reflected at the interface between the skin and air, while the remainder is refracted into the epidermis and dermis, where it is subject to scattering and absorption. Some of the scattered light undergoes multiple internal scattering events before re-emerging from the skin surface and returning to the air. This component, known as subsurface reflection, carries information about the skin's internal structure. The fractions of absorption, scattering, reflection, and refraction depend on both the properties of the incident light (e.g., wavelength, intensity, and polarization) and the optical characteristics of chromophores within the skin [42].

At the interface between two medium (e.g., the boundary between the stratum corneum and air, or between the epidermis and dermis), incident light undergoes both reflection and refraction. Reflection refers to the return of light to the original medium, whereas refraction denotes its transmission into a new medium. Most visible light that reaches the hypodermis is reflected into the dermis due to the presence of white fat deposits [43]. At the outermost skin surface, the incident light not reflected is refracted into the tissue, while the incident light reflected, referred to here as surface reflection,

comprises two components: specular and diffuse components. Specular reflection means that when light hits a surface, the light reflects at the same angle and usually occurs on smooth surfaces, such as metal; diffuse reflection implies that when light hits a surface, the light reflects in a variety of different directions and usually occurs on rough and irregular surfaces, such as paper. Reflected light from the skin includes both specular and diffuse reflection.

The light refracted into the skin tissue can give rise to subsurface reflection, which occurs when light re-emerges from the skin surface after undergoing a series of optical interactions within the skin tissue. In contrast, the surface reflection refers to the direct return of incident light to the air upon reaching the skin. Subsurface reflection results from multiple scattering events within the epidermis and dermis and contributes to the diffuse reflection [44], as shown in Figure 2-1.

Two common functions used to model skin reflectance are the bidirectional reflectance distribution function (BRDF) and the bidirectional surface scattering reflectance distribution function (BSSRDF) [45-47]. The BRDF accounts only for surface reflection, whereas the BSSRDF includes both surface and subsurface components, thus providing a more accurate representation of skin reflectance. According to Fresnel's equations, surface reflection depends on the refractive index contrast, the angle of incidence, and the polarization state of the incoming light [44]. The polarization of light is a property representing the direction of the electric field's vibration. Fresnel assumed that the incident light of a light wave is divided into p-polarized light with its electric field parallel to the plane of incidence and s-polarized light with its electric field perpendicular to the plane of incidence. The total Fresnel reflectance R for unpolarized light from air to skin is defined as the average of the reflectance values for s-polarized light R_s and p-polarized light R_p :

$$R = \frac{1}{2}(R_s + R_p) \quad (2-1)$$

$$R_s = \left[\frac{\sin(\theta_t - \theta_i)}{\sin(\theta_t + \theta_i)} \right]^2 \quad (2-2)$$

$$R_p = \left[\frac{\tan(\theta_t - \theta_i)}{\tan(\theta_t + \theta_i)} \right]^2 \quad (2-3)$$

where the θ_t and θ_i represent the angle of incidence and refraction, respectively. According to Snell's Law, when light propagates from a medium with refractive index n_1 to a medium with refractive index n_2 , the relationship between the θ_t and θ_i can be described as:

$$n_1 \sin \theta_i = n_2 \sin \theta_t \quad (2-4)$$

Then, Equation (2-1) can be rewritten as

$$R = \frac{1}{2} \left(\left[\frac{n_1 \cos \theta_i - n_2 \cos \theta_t}{n_1 \cos \theta_i + n_2 \cos \theta_t} \right]^2 + \left[\frac{n_1 \cos \theta_t - n_2 \cos \theta_i}{n_1 \cos \theta_t + n_2 \cos \theta_i} \right]^2 \right) \quad (2-5)$$

The impact of refractive index and angle of incidence on Fresnel reflection is illustrated in Figure 2-2. It should be noted that the surface reflection of the human skin does not precisely follow Fresnel's equation as the skin surface is not perfectly smooth. Surface texture, including features such as pores and wrinkles, also affects the reflection characteristics [40]. Therefore, surface texture should be considered when accurately modeling the optical properties of human skin.

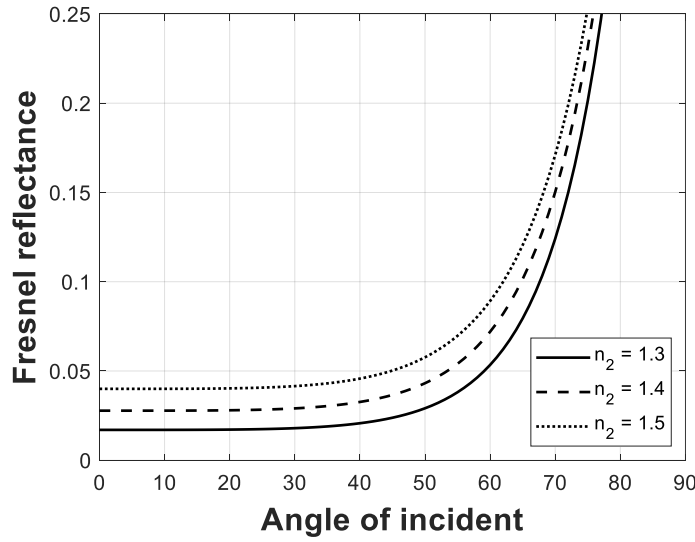


Figure 2-2 Impact of refractive index and angle of incidence on Fresnel reflection. Here, n_1 is assumed to be 1 (approximately equal to the refractive index of air), and n_2 is assumed to be 1.3 to 1.5, referring to the analysis of Lister et al. [50].

The spectral reflectance of human skin varies due to multiple influencing factors but also exhibits some consistent characteristics. Ethnicity and body location have been shown to affect skin spectral

reflectance, as demonstrated by Xiao et al. [48]. Their analysis was based on CIE XYZ values of different ethnic groups and body locations, assuming observation under illuminant D65 and using the CIE 1931 2° standard observer. However, regardless of ethnicity and body location, the spectral reflectance of human skin consistently exhibits a “W” shape in the wavelength range from 545 nm to 575 nm [49], as shown in Figure 2-3. Absorption and scattering within skin tissue play a crucial role in determining its color appearance. Absorption refers to the reduction in light intensity as it propagates through the skin, while scattering describes the changes in the direction and polarization of light during its propagation.

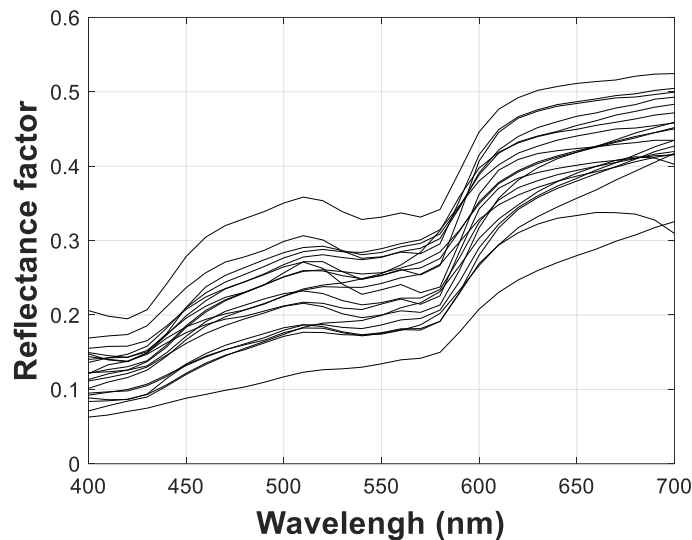


Figure 2-3 Spectral reflectance curves of twenty skin samples selected from Xiao et al.’s skin database [48], illustrating the “W” shape between 545 nm and 575 nm.

In the visible spectrum, light absorption in the skin is primarily due to melanin and hemoglobin [50]. Other substances, such as bilirubin and β -carotene, also contribute to absorption by imparting a yellow hue to the tissue [51]. However, since their concentrations are significantly lower than those of melanin and hemoglobin, Nakai et al. [52] suggested that skin color can be approximately modeled based on the absorption properties of these two major chromophores. Common skin chromophores include oxyhemoglobin, deoxyhemoglobin, melanin, bilirubin, and β -carotene. Chromophores with negligible optical effects, such as indocyanine green, are often excluded from skin color models due to their minimal contribution to light absorption [51]. The absorption coefficient is influenced by both the concentration of chromophores and the wavelength of incident light. Figure 2-4 shows the absorption

coefficient of several chromophores versus wavelength, as measured by Zijlstra et al. [53].

For instance, oxyhemoglobin has a unique absorption spectrum with a characteristic absorption peak at 420 nm and an “M” shape absorption band in the range of 545 to 575 nm [49]. This “M” shape absorption band significantly impacts the color appearance of human skin and corresponds to the “W” shape of skin color’s spectral reflectance, as shown in Figure 2-3.

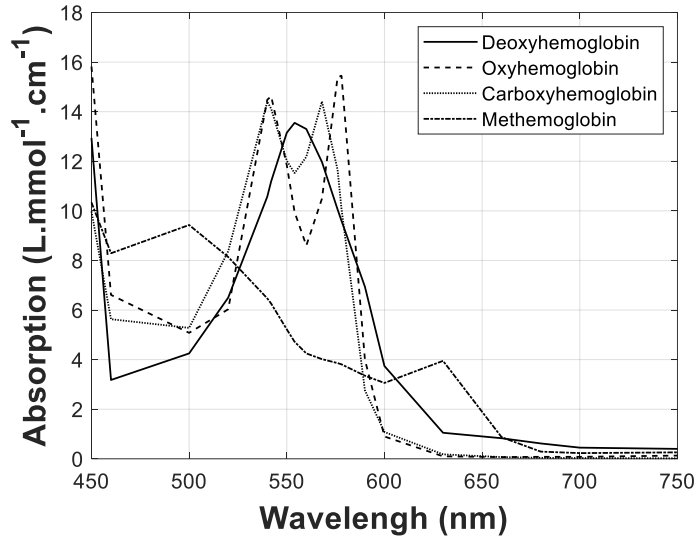


Figure 2-4 Absorption coefficients of main chromophores in skin versus wavelength, which are measured by Zijlstra et al. [53].

The absorption properties of skin tissue are described by the absorption coefficient μ_a (cm^{-1}). Each layer of human skin has a specific μ_a , representing the combined contributions of all chromophores present in that layer [51]:

$$\mu_a = \sum_i f_{v_i} \mu_{a_i} \quad (2-6)$$

where μ_{a_i} is the absorption coefficient and f_{v_i} (dimensionless) is the volume fraction of chromophore i present in this layer. Equation (2-6) can also be described by the concentration C_i (mol/L) and extinction coefficient ϵ_i ($\frac{cm^{-1}}{mol/L}$) of chromophore i :

$$R\mu_a = \ln(10) \sum_i C_i \epsilon_i \quad (2-7)$$

Scattering in human skin is mainly caused by filamentous protein. Keratin is the dominant filamentous protein in the epidermis, while collagen is the major filamentous protein in the dermis [54]. Furthermore, melanosomes, cell nuclei, cell walls, and other structures in the skin also contribute to scattering [55]. To characterize the scattering, Jacques [51] fitted the reduced scattering coefficient μ'_s (cm^{-1}) with separate contributions of Rayleigh and Mie scattering:

$$\mu'_s(\lambda) = a \left(f_{Ray} \left(\frac{\lambda}{500 \text{ (nm)}} \right)^{-4} + (1 - f_{Ray}) \left(\frac{\lambda}{500 \text{ (nm)}} \right)^{-b_{Mie}} \right) \quad (2-8)$$

where a is a scaling factor to generate a dimensionless value, f_{Ray} is the fraction of Rayleigh scattering, $(1 - f_{Ray})$ is the fraction of Mie scattering, and b_{Mie} is scattering power of Mie scattering component. A reference wavelength of 500 nm is selected for normalization. Table 2-1 summarizes fitted parameter values reported by Jacques [51] across different datasets. These parameters vary depending on the dataset. For example, Aliaga et al. [36] modeled human skin color using parameters fitted from [56], specifically: $a = 36.4$, $f_{Ray} = 0.48$, and $b_{Mie} = 0.22$. Based on all these datasets, Jacques reported the mean values of $a = 48.0$, $f_{Ray} = 0.41$, and $b_{Mie} = 0.702$.

Table 2-1 Fitted parameters of the reduced scattering coefficient according to Equation (2-8) and different datasets [51].

No.	a' (cm^{-1})	f_{Ray}	b_{Mie}	Tissue type	Reference
1	36.4	0.48	0.220	Skin	[56]
2	45.6	0.22	1.184	Skin	[57]
3	42.9	0.76	0.351	Skin	[58]
4	42.6	0.40	0.919	Skin	[59]
5	58.3	0.31	0.991	Skin	[60]
6	43.6	0.41	0.562	Dermis	[61]
7	66.7	0.29	0.689	Epidermis	[61]
Mean	48.0	0.41	0.702	N/A	N/A
SD	10.6	0.178	0.351	N/A	N/A

Chapter 3 Research gap and questions

Skin color plays a vital role across multiple disciplines, especially in color science. This thesis investigates the mechanisms, measurement, modeling, and applications of skin color through four distinct studies, each driven by a specific research motivation.

Although studied for decades, most color constancy algorithms rely heavily on various pixels to estimate illuminant chromaticities, which makes them prone to failure in scenes with large uniform areas, especially those dominated by skin colors. Gamut-based methods that incorporate skin color as a feature have shown promise in portrait images, particularly when skin colors are prominent. However, many of these methods lack comprehensive reference datasets based on real skin reflectance measurements and light sources. As a result, their performance degrades under varied lighting conditions, especially in images dominated by skin color, such as front-camera selfies or close-up portraits.

Previous research has extensively examined how the perceived white point varies under different adapting conditions, particularly in terms of adapting chromaticity, adapting luminance, viewing mode, viewing medium, and field of size. However, many of these studies relied on simplified stimuli, such as uniform color patches, or did not consider the joint effects of adapting and stimulus illuminance, limiting their applicability to real-world viewing conditions. Notably, the joint effects of adapting and stimulus illuminance have received little attention, and the specific influence of stimulus illuminance on the perception of image-based stimuli remains underexplored. This gap limits the applicability of existing findings to realistic scenarios where viewers observe full-screen images under diverse adapting conditions.

Characterizing human skin color is essential across fields such as color science, computer vision, medicine, and cosmetics. While notable progress has been made in measurement methods, biophysical understanding, and skin color modeling, key challenges persist. Current measurement techniques are limited by imaging and sensing constraints, making comprehensive and reliable facial skin data difficult to obtain. Modeling remains challenging due to trade-offs between accuracy and efficiency, often requiring complex assumptions about skin structure and composition. These issues highlight the

need for improved measurement approaches, more flexible modeling strategies, and deeper insights into the factors influencing skin color appearance.

Skin scales and skin models are two key tools in skin color characterization: skin scales offer standardized references for assessing and categorizing skin tones across populations, while skin models simulate the optical behavior of skin based on its layered structure and chromophore composition. Although their objectives are aligned and their functions complementary, existing studies have rarely considered integrating these two approaches. Most skin models are developed and validated independently of empirical skin scales, while skin scales offer limited flexibility for measurement and characterization. This separation limits both predictive accuracy and practical applicability of the skin color research.

To conclude, building on the reviewed literature and identified research gaps, this thesis undertakes four studies with distinct motivations to investigate skin color characterization and its applications. First, Chapter 4 proposes a color constancy algorithm based on skin color to estimate the illuminant chromaticities for images with extensive skin regions, such as portraits captured by the front camera. Second, Chapter 5 focuses on understanding how adapting and stimulus illuminance jointly influence perceived display white points, aiming to deepen the understanding of chromatic adaptation mechanisms. Third, Chapter 6 reviews and analyzes methods of skin color characterization, with a particular focus on measurement and modeling techniques. Finally, Chapter 7 integrates skin scales and skin models to establish a comprehensive framework for skin color characterization and validates it through a perceptual experiment.

Chapter 4 Color constancy algorithm for skin-dominant images using skin color gamut

4.1 Motivation

Color constancy refers to the perceived colors of objects maintaining relatively constant across significant changes in illuminant color and luminance level [1]. This phenomenon is produced by chromatic adaptation and memory color mechanisms which significantly impact the color perception of the human visual system. However, color sensors of digital still cameras do not naturally have these visual mechanisms. Therefore, to apply accurate white balance correction and render colors correctly in image processing, the digital still camera must estimate illumination chromaticities by simulating visual mechanisms. Precise estimation helps digital cameras display the constant color of images under varying illumination conditions.

In the past several years, the research topic of color constancy for digital cameras, also known as white balance, has been extensively studied [18, 20, 62-64]. However, these methods have not been extended to scenarios characterized by limited scene content and dominant skin colors. Specifically, images captured by front cameras often feature large areas of skin color in selfies, and facial movements are more frequent during capturing, such as in online meetings.

Therefore, further investigations using human skin colors are necessary to explore illumination estimation in images dominated by large skin regions. The aim of this study is to propose a gamut-based color constancy algorithm specifically designed for portrait images with extensive skin colors. This algorithm has built multiple reference gamuts utilizing representative datasets of light sources and skin reflectance spectra. The process of gamut mapping has been conducted in the cone contrast color space. An applicable loss function, based on the geometric characteristics of the skin chromaticity gamut, has also been designed. Finally, the performance of our algorithm has been evaluated on a public image dataset.

4.2 Method

4.2.1 Dataset preparation

This study aims to explore the potential of human skin data processed in the cone contrast color space for the white balance. The operation workflow of the proposed method is outlined in Figure 4-1. The first step in this workflow is to create the reference gamut look-up tables (RGL) and a set of color space transformation matrices M_{CST} . The next step is to convert the skin RGB values extracted from the input image to XYZ values. Then, the gamut look-up tables of the input image (IGL) are calculated. Finally, the differences between each pair in the RGL and IGL are compared, aiming to estimate the illuminant chromaticities by minimizing a specially designed loss function (defined in Section 4.2.2).

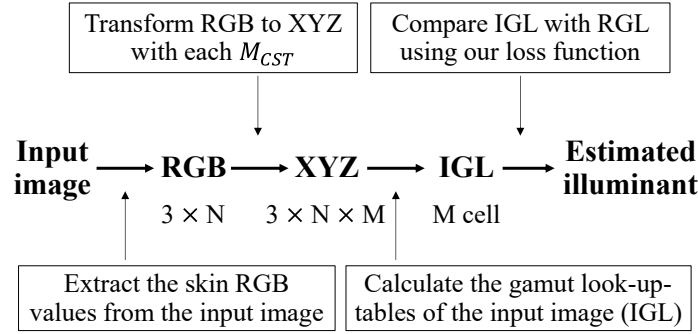


Figure 4-1 Workflow of the proposed method. N is the number of pixels in the input image. M is the number of matrices M_{CST} equal to the number of real light sources.

In this study, datasets of real light sources and skin reflectance spectra were collected. In order to generate as many gamut look-up tables as possible, a dataset of light sources [65] collected from multiple sources to cover a wide range of common light source types was selected to construct RGL and matrices M_{CST} . The correlated color temperature (CCT) range of this dataset was calculated to be from 1934 to 17183 K. Figure 4-2 shows the chromaticities of the real light sources on the CIE 1976 $u'v'$ chromaticity diagram. The hollow circles represent real light sources of the dataset, which are distributed not only along the yellow-blue axis but also along the red-green axis, with D_{uv} values ranging from -0.03 and $+0.04$. The thin black line represents the blackbody locus for reference. The chromaticities on the blackbody locus corresponding to 2000, 3000, 4000, 5000, 6000, 7000, 8000, 9000, 10000, and 20000 K are marked by filled circles. The thick black line is the upper border of the CIE 1976 $u'v'$ chromaticity diagram.

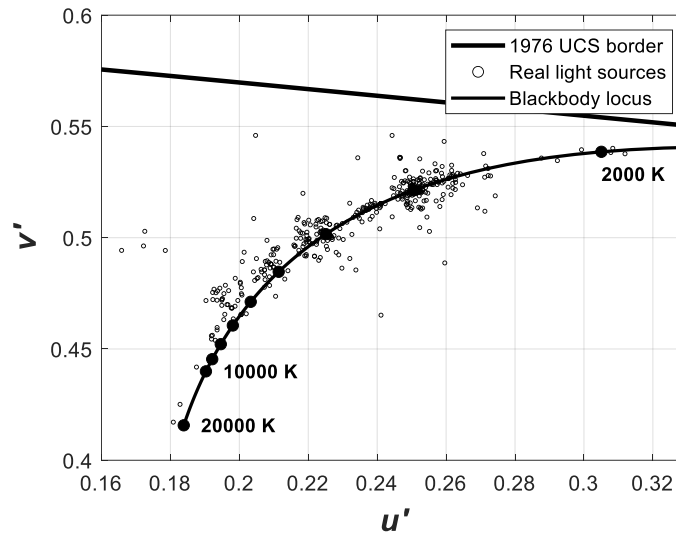


Figure 4-2 Chromaticities of real light sources on the CIE 1976 $u'v'$ chromaticity diagram.

The RGL was a reference set consisting of multiple human skin gamuts under real light sources. Each gamut in RGL was a convex hull computed by observing as many skin surfaces under a light source as possible. To make the RGL as comprehensively as possible, a skin reflectance spectra database [48], consisting of 4392 spectrophotometric measurements was used. This skin reflectance spectra database includes nine body areas (such as the forehead, cheek, and arm) of 482 subjects from three ethnic groups (Caucasians, Chinese, and Kurdish). These reflectance spectra were measured under CIE standard illuminant D65 from 360 to 740 nm in a spectral interval of 10 nm. Figure 4-3 plots all skin measurements in the chromatic a^*-b^* plane of CIELAB color space: a^* corresponds to the green-red dimension, and b^* indicates the blue-yellow dimension. The L^* , a^* , and b^* values of skin measurements were converted from XYZ values calculated using skin reflectance spectra, spectral power distribution (SPD) of D65 illuminant, and color matching functions of the CIE 1931 standard colorimetric observer. In Figure 4-3, the black dots represent skin color data, which tend to form a cluster in the chromatic a^*-b^* plane. Figure 4-4 illustrates the variation of skin chromaticity gamuts under standard illuminants A and D65. The black dash-dotted lines indicate the convex hull of the skin colors, which contains 4392 data points (black dots) inside. The shape of the skin chromaticity gamut changed with various light sources so that the light sources could be differentiated.

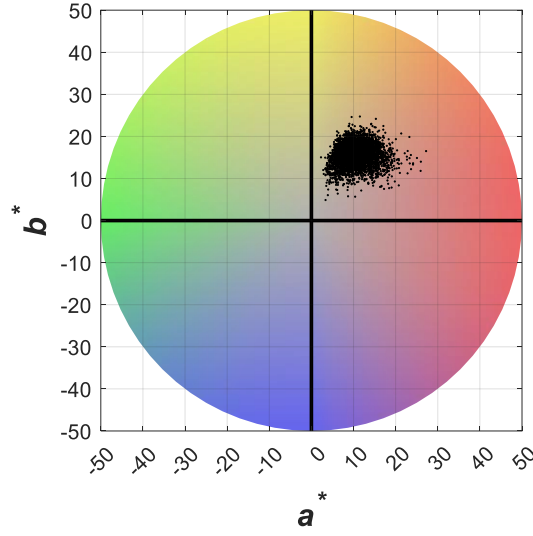


Figure 4-3 Chromaticities of 4392 skin reflectance spectra observed under illuminant D65 in the chromatic a^*-b^* plane.

In our proposed approach, a set of matrices M_{CST} was prepared before processing the input data. Matrices M_{CST} can linearly transform the color data from camera color space to CIE XYZ values under each real light source [66]. A linear 3×3 M_{CST} was derived for each light source using XYZ and RGB values of 24-patch ColorChecker and evaluated by the color difference between the calculated and the converted XYZ values. The above calculation procedure of M_{CST} is based on the spectral sensitivity-based characterization method (method A) outlined in ISO 17321-1 [67]. The M_{CST} is defined by Equations (4-1) through (4-3).

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix}_{j,i} = M_{CST} \begin{bmatrix} R \\ G \\ B \end{bmatrix}_{j,i} \quad (4-1)$$

where

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix}_{j,i} = \sum_{\lambda=380}^{780} L(\lambda) R_i(\lambda) CMF_j(\lambda) \quad (4-2)$$

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix}_{j,i} = \sum_{\lambda=380}^{780} L(\lambda) R_i(\lambda) S_j(\lambda) \quad (4-3)$$

Here, $L(\lambda)$ represents the SPD of the light sources measured under real lighting conditions. $R_i(\lambda)$

corresponds to the reflectance spectra of the 24-patch ColorChecker. CMF_j are the color matching functions of the CIE 1931 standard colorimetric observer. $S_j(\lambda)$ is the j -th channel ($j = 3$) of the camera spectral sensitivity (CSS) of Canon 5D Mark II obtained from the database of Jun Jiang et al. [68]. This CSS was measured using a monochromator and the PR655 spectrometer from 400 to 720 nm at 10 nm intervals.

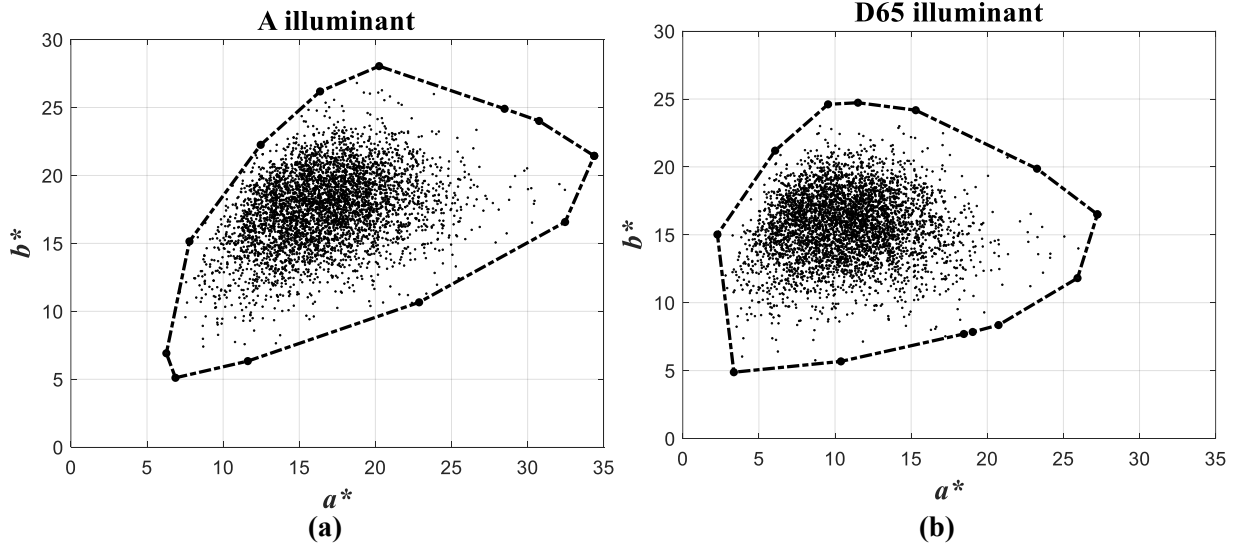


Figure 4-4 Variations of skin chromaticity gamut under illuminants A and D65.

4.2.2 Loss function

At first, our proposed method generated the corresponding IGL of the input skin data. Both the RGL and IGL were created within the cone contrast color space. In this study, “cone contrast color space” refers to the DKL cone-opponent color space, whose coordinates are defined relative to the adapting background LMS responses. The XYZ values used to create gamuts were transformed into cone fundamentals using a linear transformation proposed by Stockman and Sharpe in 2000 [69]. Although this approach represents an approximation, it provides a method for estimating cone responses from tristimulus values. Then, the cone fundamentals were transformed into the cone contrast color space, which follows the formulas in [70]. The IGL contained multiple gamuts, which matched the number of gamuts in the RGL, corresponding to the number of real light sources. The variation between each gamut pair was calculated using our proposed loss function, and the candidate light source that minimized the loss function value was selected as the estimated illuminant. Figure 4-5 shows an

example pair of gamuts, calculated under an estimated illuminant, in both the RGL and IGL.

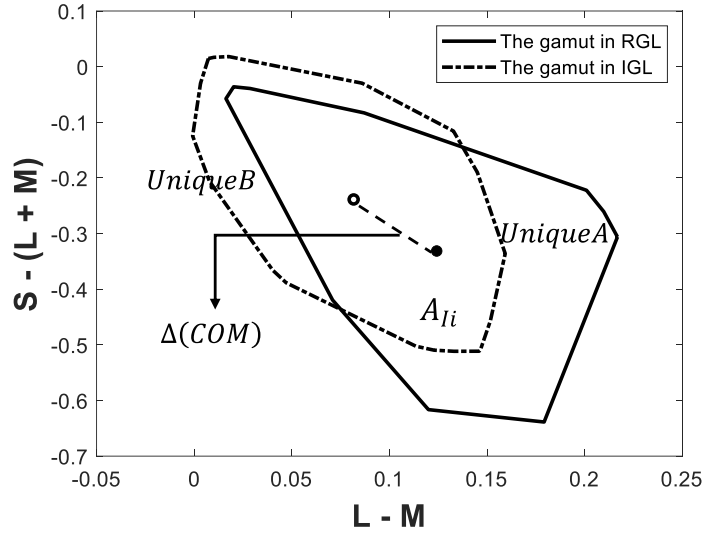


Figure 4-5 Example pair of chromaticity gamuts in the RGL and IGL. The solid line represents the gamut of skin reflectance dataset under the estimated illuminant, while the dash-dotted line represents the gamut of input skin data under the estimated illuminant.

The chromaticity gamut in the RGL represents the convex hull of the skin reflectance dataset in cone contrast color space, while the gamut in the IGL represents the chromatic distribution boundary of the input skin data. The horizontal and vertical axes correspond to two chromatic perceptual attributes of the cone contrast color space, referred to as the $L - M$ and $S - (L + M)$ opponent mechanisms. The $L - M$ opponent mechanism is defined as the difference between the L and M cone response, while the $S - (L + M)$ opponent mechanism is defined as the difference between the S cone response with a combination of L and M cone signals. It is important to note that the cone contrast color space reflects the relative contrast of stimulus to a specific background. Therefore, the cone contrast coordinates of the stimulus vary with the LMS coordinates of the adapting background. In this study, the background was set to a mid-gray, which maximizes the chromaticity gamut of the skin colors [71]. Multiple gamut features were calculated using our loss function to compare each gamut pair generated in cone contrast color space. Our proposed loss function is based on the analysis of skin gamut features from the study by Crichton et al. [24]. They designed a cost function to compute several attributes, including the planar gamut area of the input image (A_i) and the reference illuminant (A_l), the intersection area of two gamuts (A_{li}), the area of the uniquely non-overlapping gamut regions ($UniqueA$ and $UniqueB$),

the distance between their respective centers of mass ($\Delta(COM)$), and the extreme points ($\Delta(ExtP1)$, $\Delta(ExtP2)$), as defined by Equations (4-4) to (4-10):

$$\begin{aligned} \text{Cost Function [24]} &= 1 - A_{Ii} + \Delta(ExtP1) + \Delta(ExtP2) + \Delta(COM) + \\ &\quad UniqueA + UniqueB \end{aligned} \quad (4-4)$$

$$A_{Ii} = A_I \cap A_i \quad (4-5)$$

$$UniqueA = A_I - A_{Ii} \quad (4-6)$$

$$UniqueB = A_i - A_{Ii} \quad (4-7)$$

$$\Delta(ExtP1) = \sqrt{(P1_{xI} - P1_{xi})^2 + (P1_{yI} - P1_{yi})^2} \quad (4-8)$$

$$\Delta(ExtP2) = \sqrt{(P2_{xI} - P2_{xi})^2 + (P2_{yI} - P2_{yi})^2} \quad (4-9)$$

$$\Delta(COM) = \sqrt{(RG_I - RG_i)^2 + (BY_I - BY_i)^2} \quad (4-10)$$

where $P1$ and $P2$ are two extreme points of the convex hull defined in the cone-opponent color space; RG and BY represent horizontal and vertical coordinates of the center of mass in cone contrast color space. Figure 4-5 illustrates the geometric characteristics of skin chromaticity gamuts.

In our proposed loss function, the distances between the extreme points ($\Delta(ExtP1)$ and $\Delta(ExtP2)$) of two gamuts were replaced by the absolute value of the difference between two slopes ($\Delta Slope$). The slope of a gamut was obtained by performing a least-squares fit of a straight line through the origin to all points within the gamut, representing the dominant orientation of the gamut distribution. Our loss function is defined by Equations (4-11) and (4-12).

$$\text{Our Loss Function} = 1 - A_{Ii} + \Delta Slope + \Delta(COM) + UniqueA + UniqueB \quad (4-11)$$

$$\Delta Slope = |Slope_i - Slope_I| \quad (4-12)$$

4.2.3 Cross-validation on simulated data

To evaluate the feasibility of the proposed method, a five-fold cross-validation was conducted on simulated RGB skin data, calculated using the SPD of the test light sources, spectral reflectance of test

skin colors, and the CSS of the Canon 5D Mark II, as described in Equation (4-3). The estimation performances of the original cost function and our loss function were assessed using the angular error e_{ANG} [17], which is widely used in evaluating color constancy algorithms:

$$e_{ANG} = \cos^{-1} \left(\frac{e_{est} \cdot e_{gt}}{\|e_{est}\| \cdot \|e_{gt}\|} \right) \quad (4-13)$$

where e_{est} is the RGB triplet of the estimated illuminant, and e_{gt} is the RGB triplet of the ground truth illuminant. To assess the impact of the light source on estimation, the same procedure was performed on the same test set by replacing the real light sources with modeled light sources. These modeled light sources were generated using the relative SPD equations defined by CIE [72], spanning a range from 1900 to 17050 K (approximately corresponding to the minimum and maximum CCT of the real light sources) with steps of 50 K.

4.2.4 Evaluation on real image database

To evaluate the performance of the proposed method in real-world applications, a widely used dataset consisting of 568 RGB images (ColorChecker dataset) was used. This dataset includes multiple portraits representing a range of skin tones, captured both indoors and outdoors. The dataset, along with its ground truth data, was reprocessed by Hemrit et al. [73] in 2018. In this study, 55 portraits taken with a Canon 5D camera from the dataset were selected for evaluating the performance of the proposed method on real images. These portraits were limited in terms of the lighting environments they represented. Figure 4-6 shows the chromaticities of the ground truths in the ColorChecker dataset. The chromaticity coordinates of images captured by Canon 1D are marked as circles, while those of images captured by Canon 5D are shown as filled triangles.

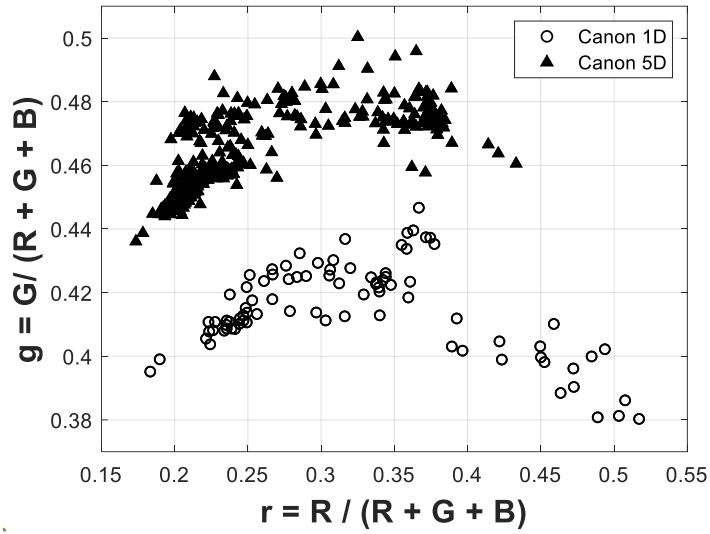


Figure 4-6 Chromaticities of the ground truths in the ColorChecker database.

Prior to evaluation, all 55 portraits were cropped to simulate front-camera selfies with a 3:4 aspect ratio, typical of an iPhone. For each portrait, a line was manually drawn connecting the two eyes, as shown in Figure 4-7(a). The horizontal distance of this line served as the unit length. The midpoint of this line defined the center of the cropped image. After cropping, each image was visually checked to confirm that all facial skin areas were included. To ensure the cropped portraits accurately reflected the area ratio of the human face to the overall image, six real selfies downloaded from the Internet were collected for comparison.

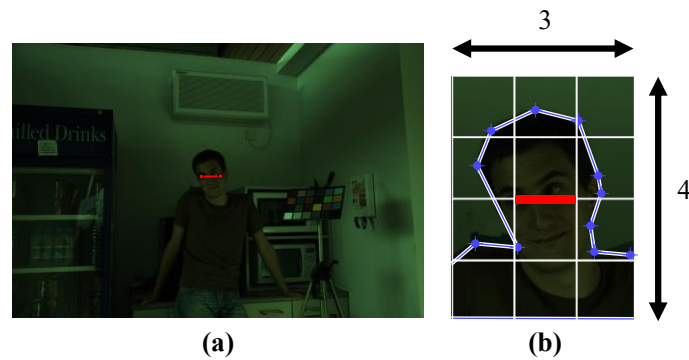


Figure 4-7 (a) Example of the facial centerline (red line) drawn on the original image. (b) Cropped image with a 3:4 aspect ratio.

The area of the human face and upper body in the image was manually selected, as shown in Figure 4-7(b). The area ratio was then calculated by comparing the area of the human portion to the total area

of the image. The average area ratio from the internet selfies was 55.5%, calculated from six images, which generally aligned with the average area ratio of our cropped images, 51.0%, calculated from 55 images. The area ratio for each cropped image is presented in Figure 4-8.

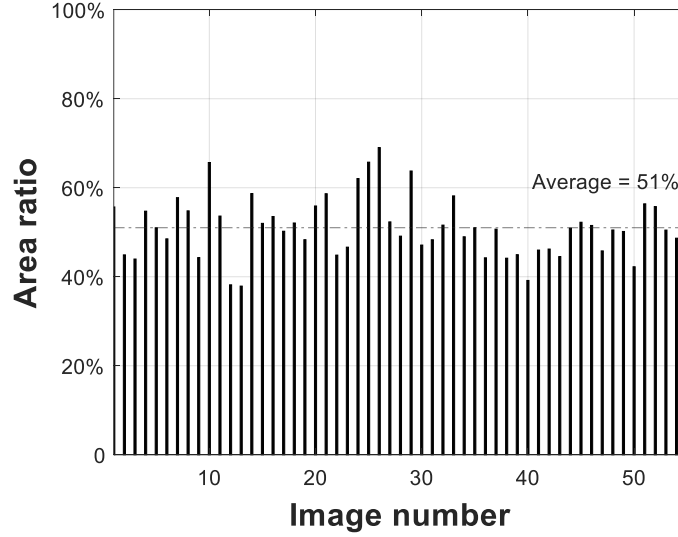


Figure 4-8 Area ratios of the human part to the cropped image for 55 portraits.

Figure 4-9 shows the chromaticities of modeled light sources, real light sources, and 55 portraits to further support this inference. The r and g chromaticity coordinates were calculated as the ratios of R and G values to the sum of R , G , and B values. The RGB values of both real and modeled light sources were obtained by transforming the corresponding XYZ values using the matrices M_{CST}^{-1} . In Figure 4-9, black dots represent the chromaticities of the modeled light sources, forming a narrow curve along the r -axis and covering only a limited region in rg space. In contrast, black crosses indicate the chromaticities of the real light sources, which span a broader region, primarily from 0.2 to 0.5 on the r -axis and from 0.42 to 0.58 on the g -axis. The chromaticities of the 55 portraits, shown as black triangles, are largely distributed within the coverage area of the real light sources, highlighting their greater diversity and representativeness.

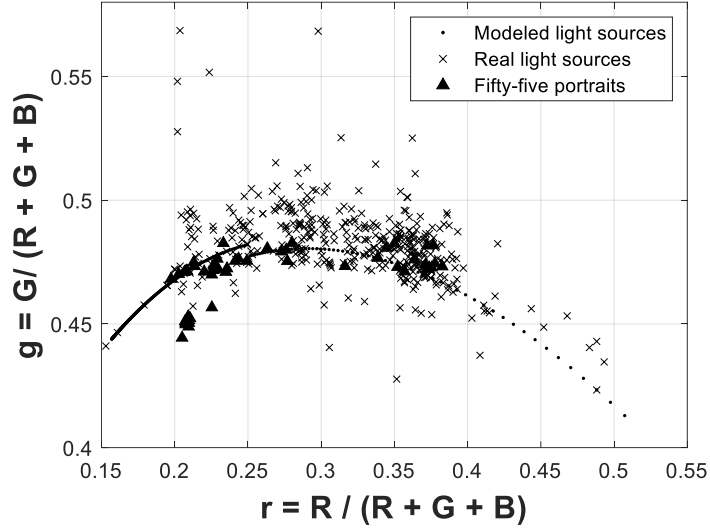


Figure 4-9 Chromaticities of modeled light sources, real light sources, and portraits.

4.3 Result

4.3.1 Result of simulated data

In the five-fold cross-validation conducted on simulated RGB values, the average angular error of the proposed method was 1.68, which was slightly higher than that of Crichton et al.'s cost function (1.11) but still below 2. When the real light sources used for constructing the RGL and M_{CSTs} were replaced with modeled light sources, while keeping the test set unchanged, the average angular error of our method increased to 5.97 for the proposed method, higher than 1.16 for Crichton et al.'s cost function. These results suggest two key observations. First, the use of modeled light sources to construct RGL and matrices M_{CST} degrades the accuracy of illuminant estimation. This may be because real light sources provide richer spectral information than modeled light sources, resulting in better estimation performance. Therefore, additional real light source datasets need to be collected in the future to construct a more comprehensive reference set of chromaticity gamuts. Furthermore, more portrait datasets should be developed to enable robust evaluation of face-based illumination estimation algorithms.

Second, Crichton et al.'s cost function consistently outperformed the proposed method, regardless of the light source type used in the RGL. One possible explanation is that the test set consists of simulated data without real-world noise. In such conditions, the Crichton et al.'s calculation of $\Delta(ExtP)$ may

retain more precise geometric information than the $\Delta Slope$ metric employed in the proposed method. The performance of the proposed method on real images is presented in next Section.

4.3.2 Result of real images

The proposed algorithm was compared against eight state-of-the-art color constancy algorithms using the angular error e_{ANG} , as defined in Equation (4-13). Table 4-1 summarizes the results, reporting the mean, median, trimean, and maximum angular errors for each method. Additionally, the mean angular errors for the best-performing 25% and worst-performing 25% of images were also computed to provide further insight into robustness.

Table 4-1 Comparison of angular errors of our method and other color constancy algorithms on the cropped images. Abbreviations of color constancy algorithms: GW, gray world [18]; WP, white patch [19]; SoG, shades of gray [20]; GGW, generalized gray world [62]; GE1, first order gray edge [63]; GE2, second order gray edge [63]; BDP, bright and dark pixels [64].

No.	Method	n	p	σ	Mean	Median	Trimean	Best 25%	Worst 25%	Max
1	GW	0	1	0	6.05	5.60	5.75	1.43	11.23	20.25
2	WP	0	∞	0	5.26	3.87	4.50	1.03	11.50	22.68
3	SoG	0	3	0	4.78	3.33	4.40	1.45	9.74	15.53
4	GE1	1	3	3	4.45	3.67	4.03	1.13	8.89	14.37
5	GE2	2	3	3	4.18	3.64	3.72	1.03	8.29	13.72
6	GGW	0	3	6	5.04	3.34	4.67	1.45	10.20	15.78
7	BDP	n=2%			4.08	2.83	3.67	0.76	8.88	12.29
8	Crichton et al. [24]	N/A			8.70	8.03	8.19	1.61	16.91	23.29
9	Crichton et al. [24] (CAT02)	N/A			8.62	8.06	8.11	1.55	16.50	23.31
10	Our method	N/A			3.80	2.28	3.10	0.90	8.72	15.55
11	Our method (CAT02)	N/A			4.86	2.35	3.96	0.94	12.21	20.34
The rank of our method					1	1	1	2	2	5

The control parameters for the other seven algorithms are provided in Table 4-1. Method eight shares a similar workflow with the proposed approach but employs the cost function introduced by Crichton et al. [24]. To address the methodological assumption regarding the transformation from CIE 1931

XYZ to cone color space, additional analysis was conducted using the CAT02 matrix from CIECAM02 as the linear transformation. The corresponding results are included in Table 4-1 as Method eleven (our method with CAT02) and Method nine (Crichton et al.'s method with CAT02). The last row of Table 4-1 presents the relative ranking of our proposed method across each statistical metric.

The proposed algorithm achieved top performance in terms of mean, median, and trimean angular errors, ranking first among all compared algorithms. In other metrics, its performance remained competitive, with angular errors closely approaching the best-performing values. These results demonstrate the robustness and accuracy of the proposed method.

In Tables 4-1, method eight represents a method using the same frame and datasets as our proposed method but using Crichton et al.'s cost function [24], as defined in Equations (4-4) to (4-10). As described in Section 4.3.1, method eight performed better than our method on the simulated RGB data. However, it is important to note that the angular errors of our method were significantly lower than those of method eight. This discrepancy supports the hypothesis that our method is more suitable for real-image scenarios. The use of a linearly fitted slope derived from skin data provides a more generalized representation of the chromaticity gamut, making the method more robust to noise commonly found in real images.

Figure 4-10 illustrates the effectiveness of our method on a selection of example images. The numerical values displayed on each image indicate the angular errors of the corresponding method. These images contain multiple skin colors of different genders and are taken under diverse illumination conditions. For improved visual clarity, gamma correction with a gamma value of 2.2 was applied to all images.

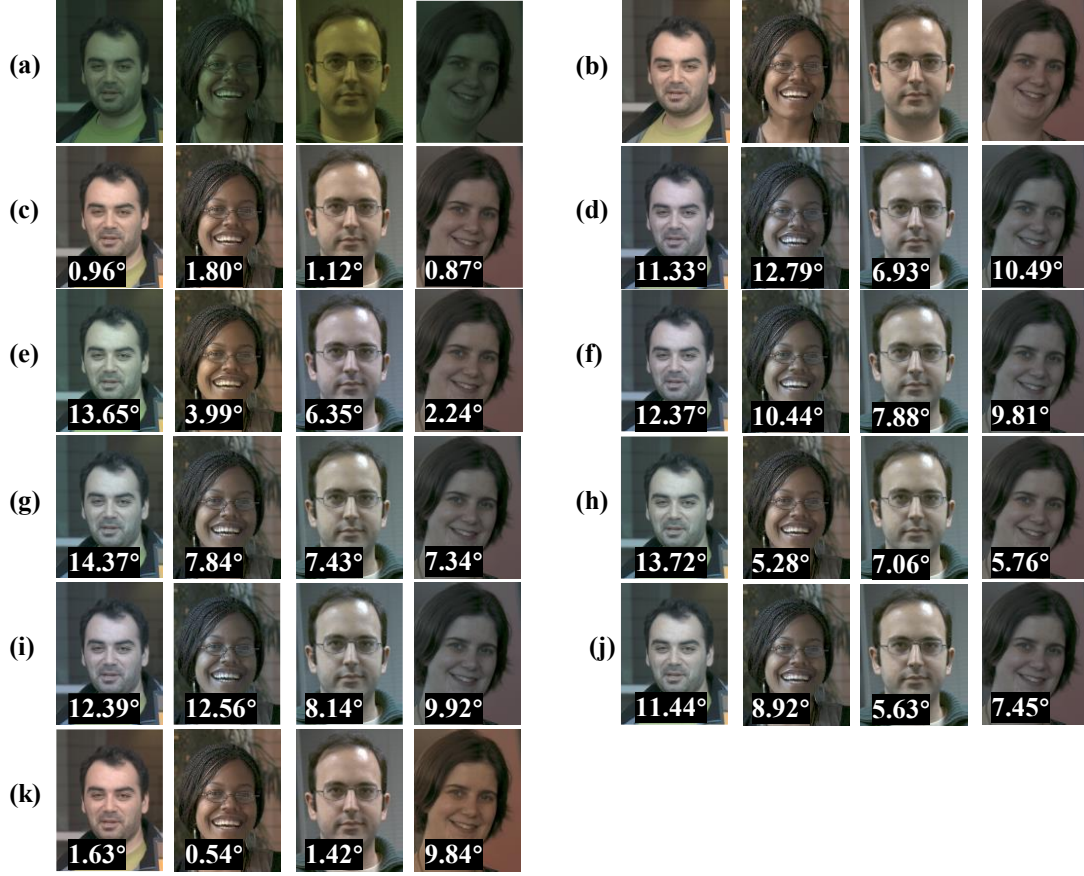


Figure 4-10 Example images of individuals with different skin colors. The subplots are: (a) the original images, (b) the images corrected using the ground truth, (c) the images corrected using our proposed method, and (d-k) images corrected using other methods corresponding to methods 1 to 8 in Table 4-1. The numerical values displayed on each image indicate the angular errors of the corresponding method.

4.4 Discussion

4.4.1 Impact of image pixels

The results presented in Table 4-1 demonstrate the strong competitiveness of the proposed method. Except for the algorithm based on Crichton et al.'s cost function, all other compared algorithms estimated illuminant chromaticities using the pixels across the entire image. Consequently, their performance may be compromised when the test image is cropped. The results of these algorithms under additional cropped situations were computed to evaluate the impact of pixels on the efficiencies of the algorithms. To evaluate the impact of pixels on the efficiencies of the algorithms, additional evaluations were conducted in which these algorithms were tested under cropped image conditions.

To further assess the robustness of each algorithm under realistic conditions, two additional cropped

conditions with the same aspect ratio (3:4) were introduced to simulate potential facial movements, such as those commonly observed during online meetings. In the second scenario, the facial centerline was horizontally shifted, while in the third, it was vertically deflected. These modifications were designed to emulate typical deviations in facial movement. Figure 4-11(a), (b), and (c) illustrate the three cropped conditions: standard, horizontal deflection, and vertical deflection. The results of the second and third cropped conditions are listed in Table 4-2 and 4-3, respectively. In the second and third cropped cases, the results of our approach still stand out. Since our method relied on extracting skin pixels from human faces, the variation in input values caused by facial movement was minimal, thereby having negligible influence on the estimation outcome.

Table 4-2 Comparison of angular errors of our method and other color constancy algorithms under the second cropped condition.

No.	Method	Mean	Median	Trimean	Best 25%	Worst 25%	Max
1	GW	5.53	5.12	5.18	1.07	10.75	19.40
2	WP	5.34	3.88	4.59	1.02	11.53	22.68
3	SoG	4.66	3.62	4.30	1.32	9.49	15.39
4	GE1	4.27	3.92	3.96	1.20	7.93	14.36
5	GE2	4.06	3.83	3.74	1.10	7.55	14.83
6	GGW	4.88	3.99	4.52	1.27	9.97	15.57
7	BDP	4.05	3.18	3.72	0.97	8.58	11.11
8	Crichton et al. [24]	8.59	8.03	8.08	1.32	16.63	23.31
9	Crichton et al. [24] (CAT02)	8.53	8.03	8.09	1.47	16.38	23.31
10	Our method	3.91	2.66	3.12	0.89	8.91	15.76
11	Our method (CAT02)	5.23	2.66	4.36	0.91	13.48	20.34
The rank of our method		1	1	1	1	4	6

The variation in algorithmic performance across different cropping conditions reflected the stability of each method. To further examine this stability, the average angular errors for each image across the three cropping conditions were calculated, as summarized in Table 4-4. Our proposed method outperformed all others in terms of mean, median, trimean angular errors, and the mean error of the

best-performing 25% of images. These results demonstrate that the proposed method not only achieves satisfactory estimation accuracy but also exhibits superior robustness.

Table 4-3 Comparison of angular errors of our method and other color constancy algorithms under the third cropped condition.

No.	Method	Mean	Median	Trimean	Best 25%	Worst 25%	Max
1	GW	6.26	5.52	6.00	2.28	10.79	19.46
2	WP	5.21	4.72	4.72	0.89	10.40	22.68
3	SoG	5.13	4.12	4.82	1.77	9.78	15.51
4	GE1	4.56	3.93	4.18	1.25	8.89	13.74
5	GE2	4.20	3.69	3.83	1.08	8.22	14.07
6	GGW	5.46	5.24	5.18	1.69	10.34	15.72
7	BDP	4.49	3.56	4.22	1.08	9.25	12.35
8	Crichton et al. [24]	8.81	8.03	8.33	1.69	17.01	23.29
9	Crichton et al. [24] (CAT02)	8.75	8.03	8.30	1.50	16.99	23.31
10	Our method	3.91	2.28	3.18	0.90	9.21	15.55
11	Our method (CAT02)	4.89	2.35	4.04	0.93	12.33	20.34
The rank of our method		1	1	1	2	3	5

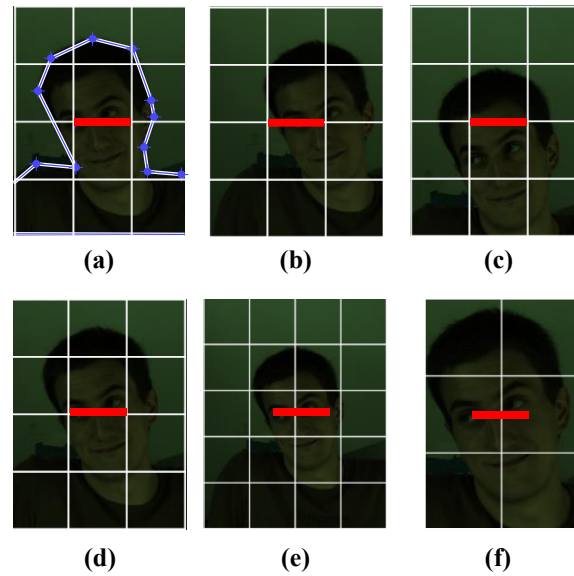


Figure 4-11 Examples images under three cropped conditions: (a) standard, (b) horizontal deflection, and (c) vertical deflection. Examples of cropped images with aspect ratios of (d) 3:4, (e) 4:5, and (f) 2:3.

Table 4-4 Comparison of angular errors of our method and other color constancy algorithms under three cropped conditions.

No.	Method	Mean	Median	Trimean	Best 25%	Worst 25%	Max
1	GW	5.95	5.39	5.63	1.76	10.66	19.71
2	WP	5.27	4.17	4.74	1.63	10.33	22.68
3	SoG	4.86	3.75	4.52	1.66	9.47	15.48
4	GE1	4.42	3.67	4.14	1.39	8.31	13.81
5	GE2	4.15	3.86	3.85	1.21	7.73	14.19
6	GGW	5.13	3.80	4.79	1.65	9.96	15.69
7	BDP	4.21	3.42	3.88	1.19	8.46	11.73
8	Crichton et al. [24]	8.70	8.03	8.18	1.63	16.70	23.29
9	Our method	3.87	2.82	3.20	0.92	8.74	15.55
The rank of our method		1	1	1	1	1	4

Subsequently, the performance of the other algorithms, which were designed to process entire images, was evaluated and analyzed. Table 4-5 reports the angular errors of the other methods when applied to uncropped images. The minimum values of each statistic in Table 4-5 are all lower than the corresponding angular errors of our method when applied to cropped images. With the exception of the “white patch” algorithm, other methods perform better on full images than cropped images, indicating that facial movement negatively influenced their accuracy. The comparatively poorer performance of the white patch algorithm may be attributed to its sensitivity to matte surfaces with high luminance but chromatic bias. The analysis presented in this section demonstrates the applicability of our proposed approach to front camera scenarios. Moreover, our method has the potential to be extended to other application scenarios where the image is not rich in content but contains human faces.

When the ratio of the human part to the image changes, the number of pixels within the cropped image also varies. The previous cropped cases all generated 3:4-ratio vertical images taking the facial centerline as the length unit. In this section, two additional cropping configurations were generated using the same length unit but with different aspect ratios. Figures 4-11(d), (e), and (f) display the

example images with aspect ratios of 3:4, 4:5, and 2:3, respectively. The area ratios of the human part to the image for each portrait under the above three aspect ratios are shown in Figure 4-12.

Table 4-5 Angular errors of other methods for uncropped images.

No.	Method	Mean	Median	Trimean	Best 25%	Worst 25%	Max
1	GW	3.62	2.74	2.95	0.69	8.12	17.46
2	WP	8.86	5.20	7.87	0.99	21.55	39.32
3	SoG	3.31	1.95	2.68	0.65	7.81	14.29
4	GE1	3.79	2.42	3.10	0.88	8.90	15.45
5	GE2	3.70	2.68	3.08	0.82	8.24	15.53
6	GGW	3.22	2.12	2.56	0.70	7.46	14.60
7	BDP	3.19	2.07	2.35	0.57	7.55	17.79

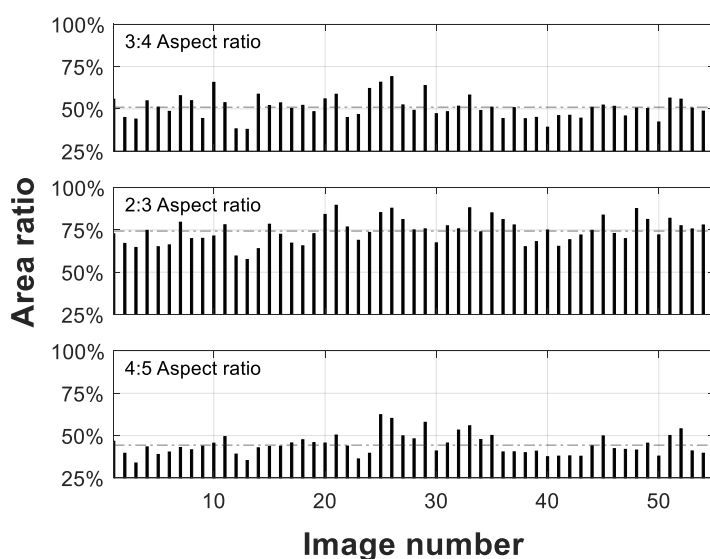


Figure 4-12 Area ratios of the human part to the images formed with aspect ratios of 3:4, 4:5, and 2:3.

The average area ratios of all images were 51.0%, 44.4%, and 74.3% for the 3:4, 4:5, and 2:3 aspect ratios, respectively. The mean angular errors of these three cases were compared, and the results are summarized in Figure 4-13. According to the results in Figures 4-12 and 4-13, the performance of the other algorithms improves as the area ratio decreases. This finding suggests that color constancy algorithms relying on the full image are less effective when estimating illuminant chromaticities from images with limited pixel content.

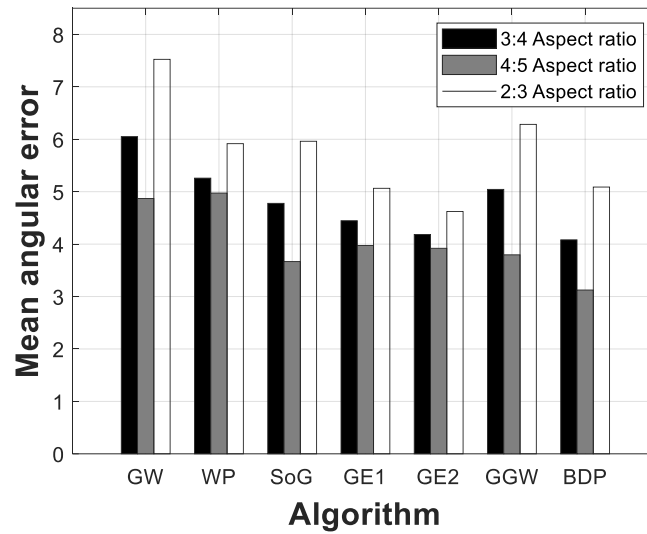


Figure 4-13 Mean angular errors of other color constancy algorithms under three aspect ratio conditions.

4.4.2 Impact of the transformation matrix from XYZ to LMS

A critical methodological consideration in this study is the transformation from CIE 1931 XYZ to the cone contrast color space. To evaluate the impact of the transformation matrix from XYZ to LMS, an analysis was conducted using the CAT02 transformation from the CIECAM02. The comparative results are summarized in Table 4-1 to 4-3 (Methods 9 and 11) and visualized in Figure 4-14.

Figure 4-14 presents a direct comparison of the angular error (AE) obtained using the two transformations. In Figure 4-14(a), representing our method, the points are predominantly located above the $y = x$ line, indicating that angular errors calculated with the CAT02 matrix are generally larger than those obtained using the Stockman and Sharpe transformation. This trend is consistent across all three cropping conditions (standard, horizontal, and vertical) and agrees with the results summarized in Table 4-1 to 4-3. In contrast, Figure 4-14(b), representing Crichton et al.'s method, shows scatter points clustered around the $y = x$ line. This suggests that the angular errors are relatively insensitive to the choice of transformation matrix for this method, implying that its performance remains largely stable regardless of which linear transformation is used to estimate cone responses.

For the proposed method, the results computed using the Stockman and Sharpe transformation generally yielded lower angular errors compared to CAT02. This trend was attributed to the fact that the Stockman and Sharpe transformation was designed based on physiological cone sensitivities and

was therefore more closely aligned with the actual cone responses of human vision. Consequently, it provided more spectral information needed for illuminant estimation, which was essential for the proposed method. In contrast, CAT02, being designed primarily for chromatic adaptation modeling, led to slightly larger angular errors in this study.

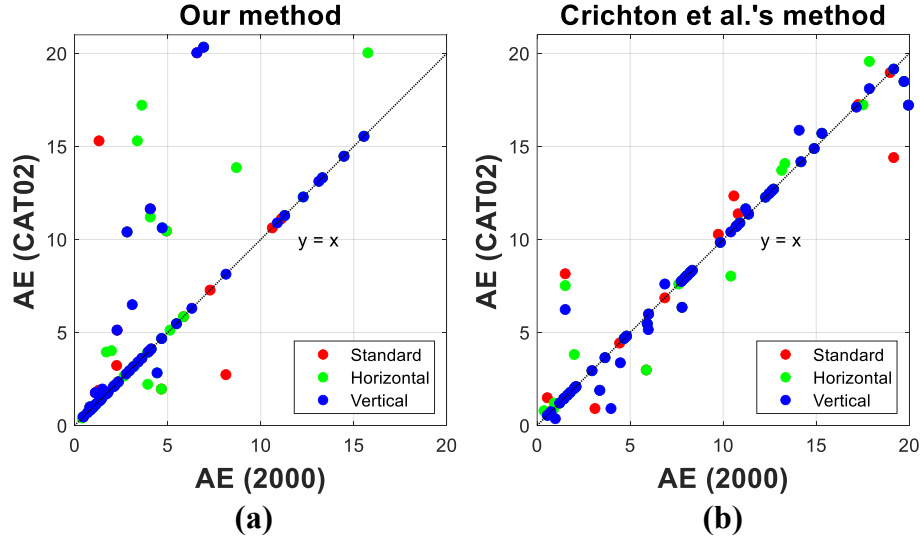


Figure 4-14 Comparison of angular errors obtained using the transformation proposed by Stockman and Sharpe in 2000 and the CAT02 matrix. (a) Our method; (b) Crichton et al.'s method. The horizontal axis represents angular errors computed using the Stockman and Sharpe transformation, while the vertical axis represents angular errors computed using the CAT02 matrix. AE: angular error. Red, green, and blue markers correspond to the three cropping conditions: standard, horizontal deflection, and vertical deflection.

4.4.3 Impact of camera spectral sensitivities

Camera spectral sensitivities (CSSs) are essential for numerous tasks in the field of color vision, as they describe the sensitivity of camera sensors to each wavelength in the visible spectrum. Among the publicly available CSS datasets, the database by Jun Jiang et al. [68] (CSSJ) and the database by Kawakami et al. [74] (CSSK) have been widely utilized [75]. There is a difference between these two databases in measurement. The CSSJ database was obtained using a monochromator combined with an integrating sphere, while the CSSK database was acquired using a whiteboard illuminated by the monochromator [76]. To investigate the impact of CCS on illumination estimation, the CSSs of Canon 5D and Canon 5D Mark II, as provided in both databases, were carefully compared.

At first, the sensitivity curves of Canon 5D Mark II included in both databases were normalized to the

range [0, 1] for comparative analysis. As illustrated in Figure 4-15(a), the two CSSs exhibit similar overall shapes and full widths at half maximum. However, the curve from CSSJ database presents more variations around the peak wavelengths, likely due to inevitable measurement errors.

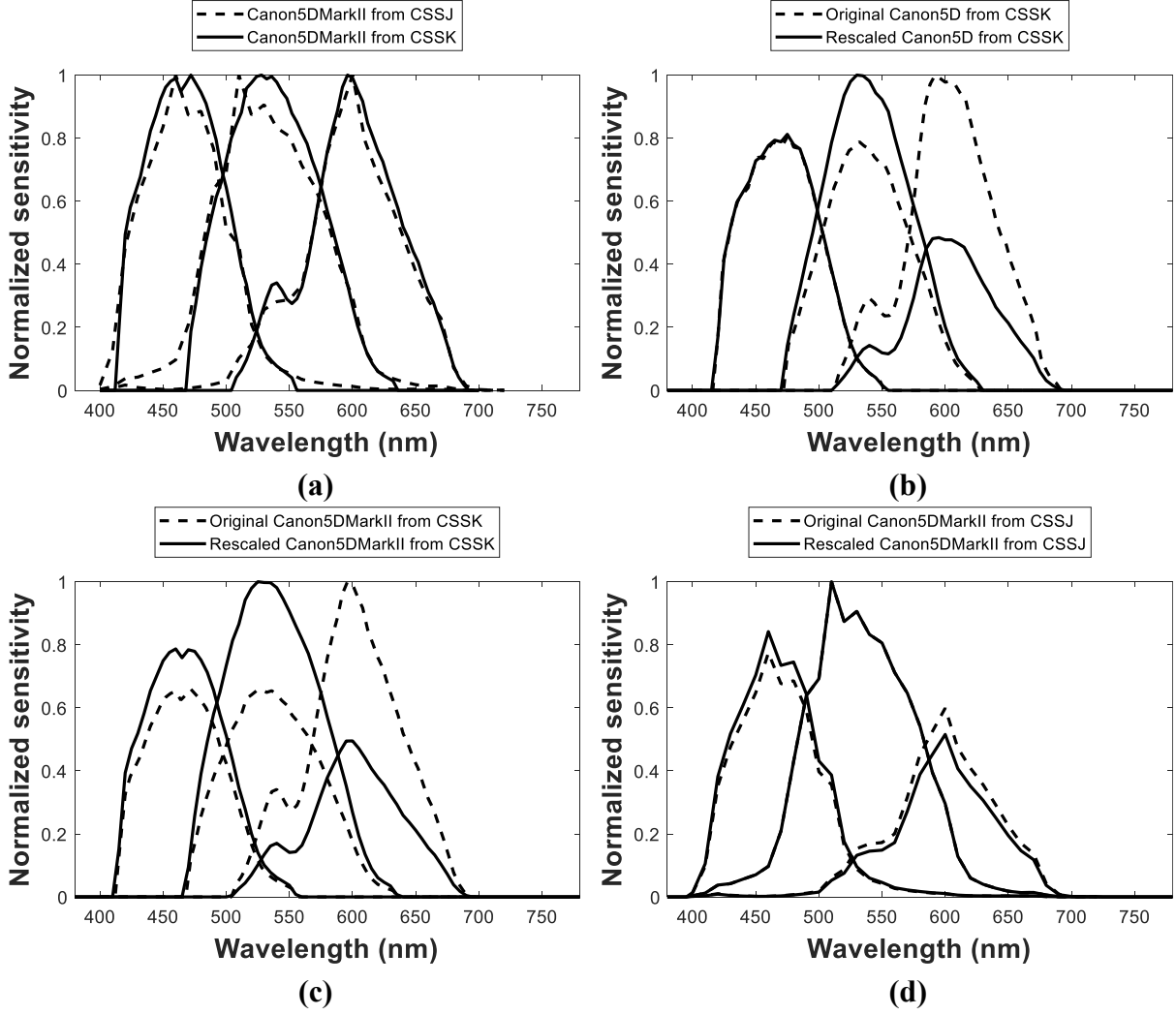


Figure 4-15 (a) Normalized sensitivity curves of Canon 5D Mark II in two databases. Original and rescaled CSSs for comparing: (b) CSSs of Canon 5D from CSSK. (c) CSSs of Canon 5D Mark II from CSSK. (d) CSSs of Canon 5D Mark II from CSSJ. CSSJ: the CSS database of Jun Jiang et al. [68]. CSSK: the CSS database of Kawakami et al. [74].

To quantify the differences between the two CSSs, the converted and calculated RGB values of the 24-patch ColorChecker under standard illuminants A and D65 were compared using angular error as the evaluation metric. The converted RGB values were transformed from the XYZ values of 24-patch ColorChecker using matrices M_{CST}^{-1} obtained from DNG files [77]. The calculated RGB values were

computed using the illuminant SPD, CCS, and reflectance spectra, as defined in Equation (4-3). Using the CSS from CSSJ database, the mean angular errors of 24 patches under illuminants A and D65 were 2.8 and 3.9, indicating spectra of the CSS from CSSJ database were fundamentally correct. In contrast, the corresponding errors using the CSS from CSSK database were higher, at 23.5 and 22.9, which is unacceptable. The primary inconsistency between CSSJ and CSSK is mainly in their RGB ratios. When normalized to the range from 0 to 1, both CSSs show similar shapes. However, in the CSS from CSSK, the B channel exhibits the strongest response, whereas the G channel is expected to dominate for a camera using an RGGB Bayer pattern. This inconsistency may result from differences in measurement setups: The CSSJ database was measured with an integrating sphere, while the CSSK database was measured using a whiteboard, which may lead to larger measurement errors.

To address this discrepancy, a rescaling procedure was applied to the CSSs to assess the influence of the measurement error. Specifically, the converted RGB values were obtained by converting the XYZ of D65 using the color matrix from the DNG file. Then, calculated RGB values were computed by applying the CSS to the SPD of D65. The rescaling factors were derived by calculating the ratio of these two RGB values. After rescaling, the mean angular errors between the converted and calculated RGB values were 3.4 (illuminants A) and 1.7 (illuminants D65) for the rescaled CSS from CSSJ, and 3.1 and 1.7 for the rescaled CSS from CSSK.

Then, the effects of the CSS on RGB values were further analyzed in two aspects: measurement errors in CSSs and camera model differences. The evaluation was based on the mean angular errors of the RGB values of the 24-patch ColorChecker under illuminants A and D65. First, the impact of measurement error was assessed, with the relevant CSSs illustrated in Figure 4-15(b–d). The mean angular errors between RGB values calculated using the original and rescaled Canon 5D CSSs from the CSSK database were 22.3 and 19.3, respectively. For the Canon 5D Mark II, the errors using CSSs from CSSK were 26.2 and 23.1, while those using CSSs from CSSJ were considerably lower, at 4.2 and 3.8. As previously discussed, the substantial errors observed with CSSK data are likely due to the fact that these CSSs do not represent the relative responses of the R, G, and B channels. Nevertheless, even for the CSSJ database, the angular errors between RGB values produced using the original and rescaled CSSs exceeded 3 degrees—commonly regarded as the upper threshold for acceptable

perturbation [78]. Second, differences between the converted RGB values of Canon 5D (from CSSK only) and Canon 5D Mark II (from both CSSK and CSSJ) were examined using the rescaled CSSs. The corresponding mean angular errors are summarized in Table 4-6. Comparisons involving CSSs from the same database yielded slightly lower angular errors than those from different databases. Overall, the angular errors introduced by differences in camera models were consistently around 3 degrees (ranging from 2.7 to 3.5). This analysis of a specific case indicates that measurement errors in CSS acquisition may have a more pronounced effect on illumination estimation than those arising from differences between similar camera models.

Table 4-6 Angular errors between the converted RGB values of rescaled Canon 5D (from CSSK only) and those of rescaled Canon 5D Mark II (from CSSK and CSSJ).

		Canon 5D from CSSK	
		Under standard A illuminant	Under standard D65 illuminant
Canon 5D Mark II	From CSSK	2.7	2.8
	From CSSJ	3.0	3.5

4.5 Conclusion

Most color constancy algorithms are proposed for images captured by common digital cameras. However, these algorithms often fail in scenarios involving images dominated by large skin colors, such as those captured by front cameras. Although certain gamut-based algorithms utilize specific features such as skin colors to estimate the illuminant chromaticities, their effectiveness remains limited due to insufficient reference gamuts and their lack of suitability for skin-dominant scenes.

This study explored the potential of using human facial skin data, processed in cone contrast color space for illumination estimation. Reference gamut look-up tables were constructed using a database of skin reflectance spectra and a database of real light sources. A carefully designed loss function was introduced to estimate illuminant chromaticities by calculating multiple gamut features of the input skin data. To evaluate the feasibility of the proposed method, five-fold cross-validation was performed on simulated skin RGB data. Furthermore, fifty-five images from a publicly available dataset were cropped to simulate front camera conditions and used to compare the performance of the proposed method against existing algorithms.

The results indicate that the proposed method provides accurate and reliable estimations for images dominated by large skin colors. The wide range of chromaticities in the real light source database used for constructing the reference gamuts appears to enhance the algorithm’s performance, suggesting that the collection of more real light source datasets would be beneficial. Multiple sets of cropped images were generated to assess the effect of the area ratio of the human region to the overall image on algorithm performance. The results demonstrate that the proposed method is particularly effective for images with limited content but containing skin regions. In addition, the proposed loss function offers improved discrimination between the test and candidate illuminants.

Our method depends heavily on the accessibility and accuracy of the CSS. The influence of CSS on our approach was analyzed from two perspectives: measurement errors and variations between camera models. In this study, measurement errors were found to introduce greater angular errors than differences observed between similar camera models. The acquisition of sensitivity curves is constrained by the limitations of specialized instruments and inherent measurement inaccuracies, which inevitably impact estimation accuracy. However, the angular errors between our estimations and the ground truth remained smaller than those reported by most existing color constancy algorithms. This suggests that, with ongoing advancements in measurement technology, our method holds significant potential for application in white balance correction for skin-dominant images.

Chapter 5 Effect of adapting and stimulus illuminance on perceived display white point

5.1 Motivation

The display white point refers to the chromaticity coordinates of the reference white shown on a screen. It plays a critical role in accurate color reproduction and the overall visual experience. Specifically, the display white point can be used to ensure that colors are accurately rendered, for example, white objects still appear white on the display. Achieving the correct white point prevents unnatural color casts, thereby contributing to improved image quality and enhanced visual perception.

The white point perceived by the human eye is influenced by various environmental factors. While previous studies have examined the effects of adapting CCT and illuminance on the perceived white point of the display [79-81], most did not consider the joint influence of adapting and stimulus illuminance, nor did they investigate how stimulus illuminance affects perception when viewing image-based stimuli. This chapter explores perceived display white points across a broader range of adapting illuminance and CCT combinations, using full-screen image stimuli. Understanding how perceived display white point changes under practical viewing conditions is essential for advancing the understanding of chromatic adaptation and enhancing user experience.

Therefore, this study conducted two experiments. The first experiment aimed to investigate the display white point under different adapting conditions and produced a practical look-up table (LUT) that recommends display white points based on adapting CCT and illuminance. The second experiment validated these findings through a perceptual evaluation using the method of magnitude estimation.

5.2 Experiment I: achromatic matching of display white point

5.2.1 Method

A viewing booth with dimensions of 60 cm (width) $\times$ 60 cm (depth) $\times$ 60 cm (height) was used in the experiment. The interior surfaces of the booth were coated with Munsell N7 spectrally neutral paint. A four-channel (RGBW) spectrally tunable LED device, mounted on the booth, provided uniform

adapting illumination. A 45° angled viewing table was placed inside the booth, with a smartphone (vivo X90) positioned vertically at its center. A chin rest was installed outside the front opening of the booth to ensure consistent viewing geometry, corresponding to a field size of $10.6^\circ \times 23.2^\circ$. The smartphone display was chromatically characterized using the gain–offset–gamma (GOG) model [82]. Figure 5-1 illustrates the experiment setup from the observer’s point of view.



Figure 5-1 Experimental apparatus used in Experiment I.

The experiment included forty-four adapting conditions, including forty-two arranged in a 6×7 factorial design, one dark condition, and one additional condition to simulate overcast ambient (6500 K at 12000 lx). These latter two conditions were included to represent common real-world scenarios. Specifically, the factorial design consisted of six illuminance levels (30, 80, 330, 1000, 5000, and 15000 lx) and seven CCT levels (2500, 2700, 3500, 5000, 6500, 8000, and 10000 K). Figure 5-2 illustrates all adapting conditions except the dark condition. The display illuminance was set by the display’s auto-brightness feature, which defines the relationship between ambient and display illuminance, as shown in Figure 5-3. Corresponding to the six adapting illuminance levels, the display illuminance values were 188, 232, 330, 578, 1571, and 2435 lx, respectively. In the dark condition, the display illuminance was 6 lx, and in the overcast condition (6500 K at 12000 lx), it was 2388 lx. The illuminance level of 330 lx was carefully selected to investigate perceptual changes when display and ambient illuminance were equal and to serve as a transition point for linear interpolation in the LUT.

All adapting conditions were calibrated by adjusting the digital values of the four LED channels to achieve the target adapting illuminance and chromaticity. The photometric and colorimetric characteristics of all adapting conditions are summarized in Table 5-1.

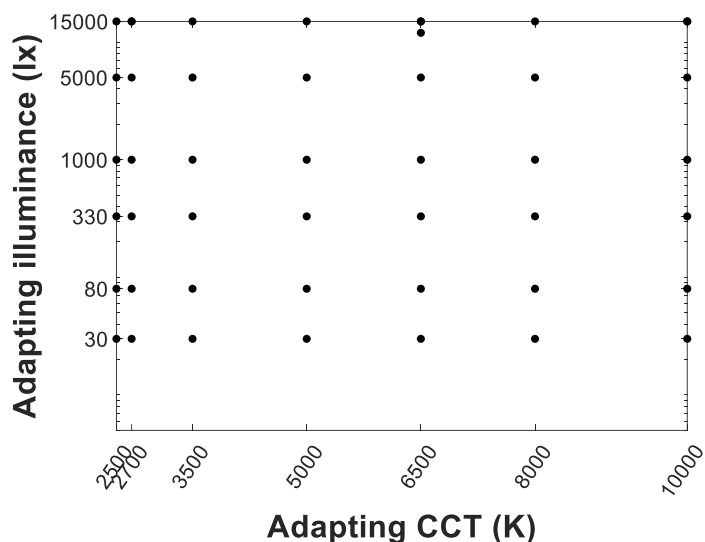


Figure 5-2 All adapting conditions in Experiment I except the dark condition.

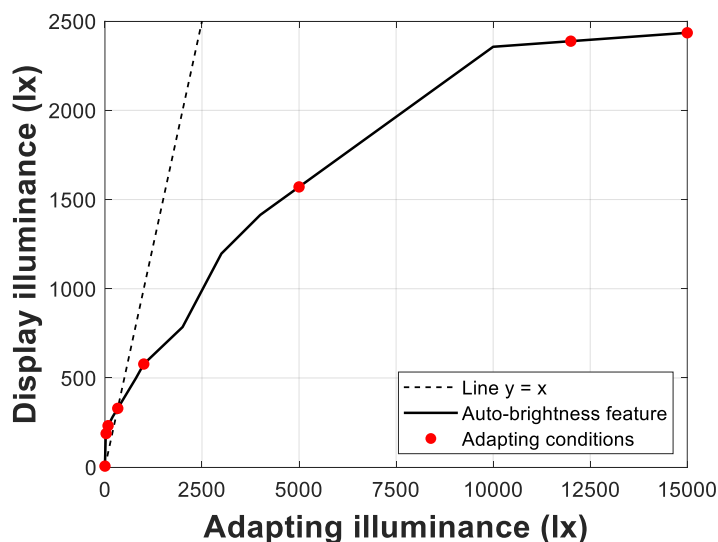


Figure 5-3 Auto-brightness feature of the display (vivo X90) used in Experiment I. The red circles represent the adapting conditions in Experiment I. The illuminance level of 330 lx was carefully selected to ensure that the display and ambient illuminance were equal.

As shown in Figure 5-4(a), two types of images, webpage and icon image, were used to simulate common smartphone interfaces. A total of 2439 chromaticity coordinates were selected as background

colors, covering a CCT range from 2500 to 15000 K and a D_{uv} range from -0.03 to $+0.03$. These coordinates were generated in a step of 0.002 along the u' and v' axes, centered around D65. All chromaticities are uniformly distributed in the CIE 1976 $u'v'$ chromaticity diagram, as shown in Figure 5-4(b). A control program, developed based on the GOG model, allowed the background chromaticity to be adjusted along the u' and v' axes using four arrow keys (i.e., down for $-v'$, up for $+v'$, left for $-u'$, and right for $+u'$), with each keypress corresponding to a step of 0.002 at a fixed illuminance level. These four directions shifted the color appearance toward blue, red, yellow, and green, respectively.

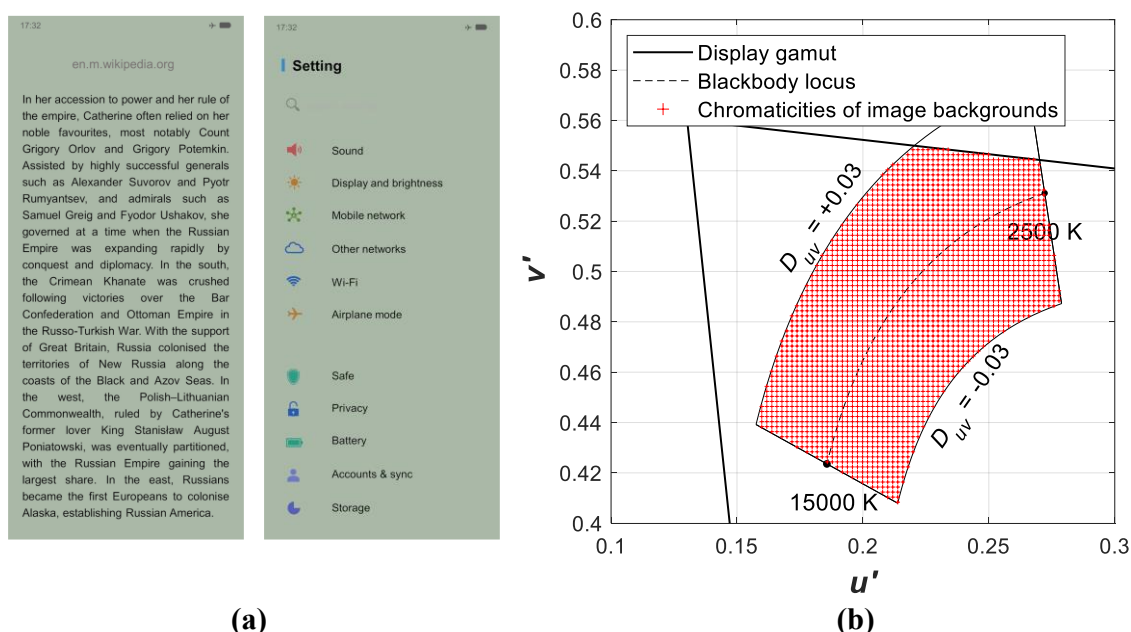


Figure 5-4 (a) Two types of images, webpage and icon image, were used in Experiment I. (b) Chromaticity distribution of the image background in the CIE 1976 $u'v'$ chromaticity diagram.

Nine observers (six males and three females), aged between 25 and 30 years (mean = 26.8, SD = 1.56), participated in Experiment I. All observers had normal color vision. The display was warmed up for 30 minutes before the experiment. Upon arrival, each observer was informed of the experimental procedure and tested using the Ishihara plates. After completing an information form, the observer was instructed to look into the viewing booth for 90 seconds (2 minutes under the dark condition) to achieve a stable state of chromatic adaptation [7]. Observers were asked to place their chins on the chin rest to ensure consistent viewing geometry. During this adaptation period, the display screen was turned off, while the general ambient illumination remained switched off throughout the experiment.

Table 5-1 Photometric and colorimetric characteristics of all adapting conditions.

Condition	Nominal illuminance (lx)	Nominal CCT (K)	Nominal CIE 1976 (u' , v')		Illuminance (lx)	CCT (K)	D_{uv}	CIE 1976 (u' , v')	
1	Dark	N/A	N/A	N/A	0	N/A	N/A	0.273	0.532
2	30	2500	0.272	0.531	29	2491	+0.000	0.263	0.528
3		2700	0.262	0.527	29	2687	+0.000	0.235	0.513
4		3500	0.236	0.511	31	3521	-0.001	0.212	0.483
5		5000	0.211	0.485	29	5006	-0.001	0.200	0.465
6		6500	0.200	0.466	31	6558	-0.001	0.194	0.455
7		8000	0.195	0.452	31	7781	-0.002	0.191	0.440
8		10000	0.190	0.440	31	9851	+0.000	0.273	0.532
9	80	2500	0.272	0.531	78	2497	-0.001	0.272	0.532
10		2700	0.262	0.527	78	2715	-0.001	0.262	0.528
11		3500	0.236	0.511	78	3413	-0.002	0.239	0.510
12		5000	0.211	0.485	79	5095	-0.001	0.211	0.482
13		6500	0.200	0.466	82	6629	-0.001	0.201	0.463
14		8000	0.195	0.452	83	8294	-0.003	0.191	0.452
15		10000	0.190	0.440	82	10262	+0.000	0.190	0.439
16	330	2500	0.272	0.531	330	2496	+0.000	0.272	0.532
17		2700	0.262	0.527	327	2692	+0.000	0.263	0.528
18		3500	0.236	0.511	331	3427	-0.001	0.238	0.511
19		5000	0.211	0.485	331	5000	-0.002	0.213	0.482
20		6500	0.200	0.466	331	6578	-0.002	0.202	0.463
21		8000	0.195	0.452	333	8223	-0.001	0.195	0.450
22		10000	0.190	0.440	333	10329	-0.001	0.191	0.438
23	1000	2500	0.272	0.531	1006	2488	+0.000	0.273	0.531
24		2700	0.262	0.527	994	2689	+0.000	0.263	0.528
25		3500	0.236	0.511	1002	3501	-0.001	0.236	0.510
26		5000	0.211	0.485	1008	5036	-0.001	0.212	0.483
27		6500	0.200	0.466	1009	6599	-0.001	0.201	0.464
28		8000	0.195	0.452	1010	8227	-0.001	0.195	0.450
29		10000	0.190	0.440	1015	10271	-0.001	0.191	0.438
30	5000	2500	0.272	0.531	5035	2490	+0.000	0.273	0.531
31		2700	0.262	0.527	5019	2690	+0.000	0.263	0.528
32		3500	0.236	0.511	5020	3504	+0.000	0.236	0.511
33		5000	0.211	0.485	5038	5057	-0.001	0.211	0.483
34		6500	0.200	0.466	5029	6628	-0.001	0.200	0.464
35		8000	0.195	0.452	5020	8202	-0.001	0.195	0.450
36		10000	0.190	0.440	5009	10509	-0.001	0.190	0.437
37	12000	6500	0.200	0.466	12057	6597	-0.001	0.201	0.464
38	15000	2500	0.272	0.531	15060	2494	+0.000	0.273	0.531
39		2700	0.262	0.527	15046	2699	+0.000	0.263	0.528
40		3500	0.236	0.511	15018	3514	+0.000	0.236	0.510

Condition	Nominal illuminance (lx)	Nominal CCT (K)	Nominal CIE 1976 (u' , v')		Illuminance (lx)	CCT (K)	D_{uv}	CIE 1976 (u' , v')	
41		5000	0.211	0.485	15034	5058	-0.001	0.211	0.483
42		6500	0.200	0.466	15063	6587	-0.001	0.201	0.464
43		8000	0.195	0.452	15044	8188	-0.001	0.195	0.450
44		10000	0.190	0.440	15067	10299	-0.001	0.191	0.438

After chromatic adaptation, the webpage image was displayed in full screen on the smartphone. The observer was instructed to adjust the background color of the image to appear as white as possible using the four arrow keys on a keyboard. There was no time constraint for this adjustment. For each adjustment, the background white point was initially set to D65. The computer program controlled the smartphone to display the image with adjusted chromaticities according to the signal from the keyboard. Once satisfied, the observer confirmed the adjustment by pressing the Enter key. Upon completion of the webpage task, the icon image was displayed with a D65 background. The same adjustment procedure was repeated under each adapting condition. All adapting conditions were grouped by illuminance level and ordered from low to high; the order of conditions within each group was randomized. To evaluate intra-observer variability, three adapting conditions (CCTs of 2700, 6500, and 10000 K at 15000 lx) were randomly selected to repeat.

5.2.2 Result

Due to potential discrepancies between the image background rendered by the GOG model and the chromaticities adjusted by the observer, all adjusted backgrounds were measured using a spectroradiometer after the experiment.

For measurement purposes, pure-color background images were generated without any content but with the same chromaticities and dimensions as those used during the experiment. Once all observers had completed their sessions, these pure-color background images were displayed under the corresponding adapting conditions, and their SPDs were measured from the observer's eye position. Subsequent analyses were based on the measured SPDs.

The average absolute luminance difference between the measured and target image backgrounds was 2.03% (SD = 1.54%). The average chromaticity difference was 0.0091 (SD = 0.0025) in the CIE 1976

$u'v'$ chromaticity diagram. All adjusted chromaticities remained well within the display gamut, indicating the reliability of the control program.

The intra- and inter-observer variations were evaluated for all the adapting conditions in terms of the mean color difference from the mean (MCDM) [83] in the CIE 1976 $u'v'$ units. A larger MCDM indicates greater variation, both for intra and inter-observer variations.

Three adapting conditions were repeated to evaluate intra-observer variation. These conditions corresponded to CCTs of 2700, 6500, and 10000 K under an illuminance of 15000 lx. For each repeated condition i ($N_i = 3$), each observer completed two adjustments ($N_n = 2$). The intra-observer variation was computed as the color difference between the chromaticities of the two adjustments and their average. The intra-observer variation over all observers ($N_m = 9$) was calculated. The final intra-observer variation was estimated by averaging the MCDM values across the three repeated conditions, as shown in Equation (5-1).

$$MCDM_{intra} = \sum_{i=1}^{N_i} \left(\sum_{m=1}^{N_m} \left(\sum_{n=1}^{N_n} \left(\sqrt{(u'_{m,i,n} - \overline{u'_{m,i}})^2 + (v'_{m,i,n} - \overline{v'_{m,i}})^2} \right) / N_n \right) / N_m \right) / N_i \quad (5-1)$$

The intra-observer MCDM values ranged from 0.0037 to 0.0059 for the webpage image, with an average of 0.0044, and from 0.0029 to 0.0048 for the icon image, with an average of 0.0037. The inter-observer variation was characterized by calculating the color differences between the chromaticities of each observer's adjustment ($N_m = 9$) and the average chromaticities across all observers (i.e., the average observer) under each adapting condition ($N_k = 44$), as described below:

$$MCDM_{inter} = \sum_{k=1}^{N_k} \left(\sum_{m=1}^{N_m} \left(\sqrt{(u'_{m,k} - \overline{u'_k})^2 + (v'_{m,k} - \overline{v'_k})^2} \right) / N_m \right) / N_k \quad (5-2)$$

The inter-observer MCDM values ranged from 0.0044 to 0.0200 for the webpage image, with an average of 0.0101, and from 0.0043 to 0.0175 for the icon image, with an average of 0.0096. All inter-observer MCDM values for both the webpage and icon images are summarized in Tables 5-2 and 5-3, respectively.

Table 5-2 Inter-observer variations of the webpage image under each adapting condition in Experiment I. The inter-observer variations were characterized by the mean color difference from the mean (MCDM) in the CIE 1976 $u'v'$ chromaticity diagram.

Adapting luminance (lx)	Adapting CCT (K)						
	2500	2700	3500	5000	6500	8000	10000
Dark				0.0156			
30	0.0081	0.0098	0.0054	0.0086	0.0076	0.0081	0.0064
80	0.0136	0.0106	0.0114	0.0077	0.0071	0.0055	0.0061
330	0.0166	0.0139	0.0103	0.0065	0.0044	0.0057	0.0082
1000	0.0163	0.0133	0.0092	0.0094	0.0046	0.0071	0.0078
5000	0.0196	0.0179	0.0130	0.0075	0.0066	0.0099	0.0080
12000	N/A	N/A	N/A	N/A	0.0065	N/A	N/A
15000	0.0200	0.0182	0.0162	0.0103	0.0073	0.0094	0.0096

Table 5-3 Inter-observer variations of the icon image under each adapting condition in Experiment I. The inter-observer variations were characterized by the mean color difference from the mean (MCDM) in the CIE 1976 $u'v'$ chromaticity diagram.

Adapting luminance (lx)	Adapting CCT (K)						
	2500	2700	3500	5000	6500	8000	10000
Dark				0.0100			
30	0.0092	0.0073	0.0068	0.0088	0.0087	0.0068	0.0080
80	0.0129	0.0111	0.0091	0.0072	0.0068	0.0051	0.0060
330	0.0144	0.0163	0.0131	0.0071	0.0044	0.0043	0.0086
1000	0.0133	0.0135	0.0099	0.0069	0.0048	0.0048	0.0059
5000	0.0175	0.0170	0.0127	0.0082	0.0067	0.0093	0.0082
12000	N/A	N/A	N/A	N/A	0.0076	N/A	N/A
15000	0.0166	0.0171	0.0147	0.0107	0.0069	0.0104	0.0079

Figure 5-5 shows the average chromaticities of the two images adjusted by each observer under different adapting conditions, along with the corresponding one-standard-deviation ellipses [84], plotted in the CIE 1976 $u'v'$ chromaticity diagram. The chromaticities were generally distributed along the blackbody locus, with the mean D_{uv} value of all results being 0.0012 and the 95% confidence interval of all D_{uv} values ranging from 0.0007 to 0.0017. Under adapting illuminance levels of 30 and

80 lx, the ellipses were tightly clustered and relatively small. In general, the size of the ellipses along the blackbody locus increased with adapting illuminance. Furthermore, lower adapting CCT values, especially 2500 and 2700 K, resulted in larger ellipses compared with higher CCT values under the same illuminance level. The sizes of the ellipses, as well as the intra-observer and inter-observer MCDM values, were comparable with those reported in recent studies that examined the display white point using the memory color matching method [79, 85].

Figure 5-6 shows the average chromaticities of the two images adjusted by all observers under different adapting CCTs but the same adapting illuminance, plotted in the CIE 1976 $u'v'$ chromaticity diagram. The red vectors in Figure 5-6 indicate the shifts in white point chromaticities at each illumination level, with vector directions pointing from lower to higher CCT values. The chromaticities adjusted under the dark condition clustered around the 6500 K region and above the blackbody locus, whereas those under the overcast condition were located near 8000 K, close to the chromaticities adjusted at 6500 K and 15000 lx.

The direction and length of the vectors are influenced by the adapting illuminance. Under high adapting illuminance, the cumulative length of all vectors is greater than that under low adapting illuminance. This indicates that the shift of the white point caused by increasing the adapting CCT from low to high is more pronounced at higher illuminance levels. The largest white point shift due to adapting CCT occurred at 15000 lx, while the smallest shift occurred at 30 lx. The effect of adapting illuminance on white point shifts is shown in Figure 5-7. The shift caused by changes in adapting illuminance was greatest at 2500 K and smallest at 8000 K. The white point CCTs under 8000 K adapting conditions remained nearly constant and closely matched the adapting CCT. The magnitude of white point shifts decreased as adapting CCT increased from 2500 to 8000 K and then increased as adapting CCT changed towards 10000 K. The vector directions were also affected by adapting CCT. At adapting CCTs of 2500, 2700, 3500, and 10000 K, increasing adapting illuminance caused the white point to shift toward the adapting CCT. In contrast, at adapting CCTs of 5000 and 6000 K, the white point shifted toward higher CCT values, moving away from the adapting CCT.

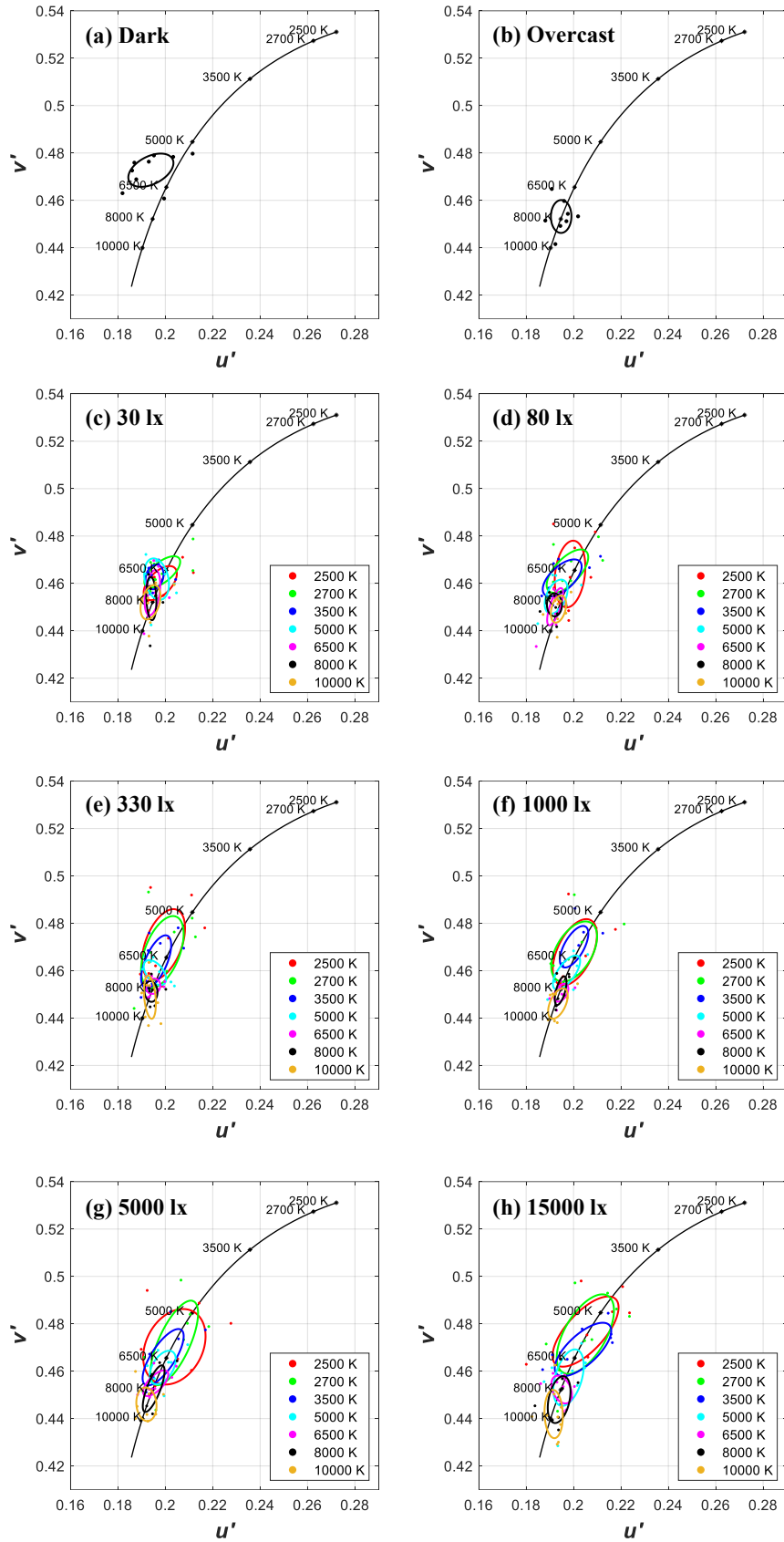


Figure 5-5 Average chromaticities of two images under different adapting conditions with the one-standard-deviation ellipses, in the CIE 1976 $u'v'$ chromaticity diagram: (a) dark, (b) overcast, and adapting illuminance of (c) 30, (d) 80, (e) 330, (f) 1000, (g) 5000, and (h) 15000 lx.

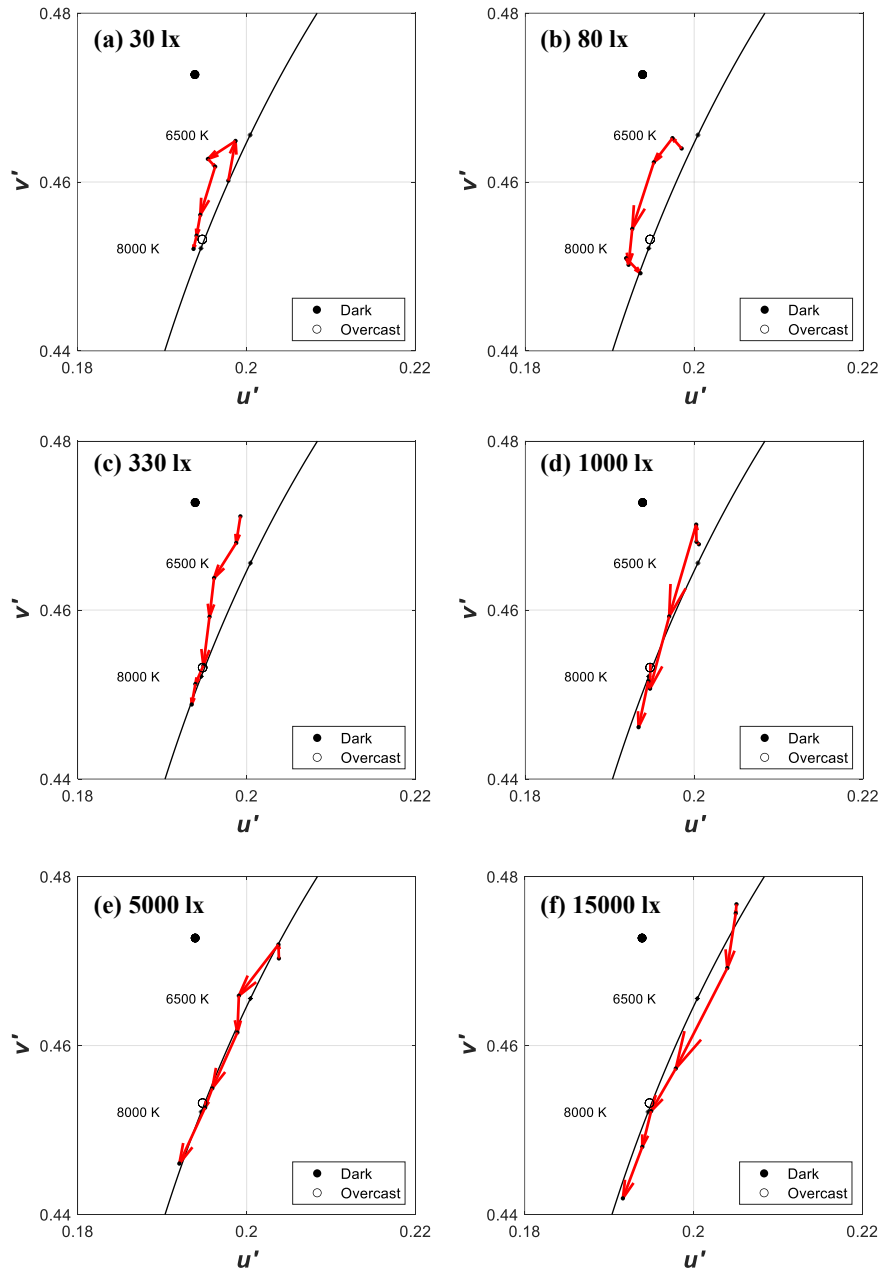


Figure 5-6 Average chromaticities at constant illuminance with varying adapting CCTs, showing white point shifts (red vectors) in the CIE 1976 $u'v'$ diagram. Conditions: (a) 30, (b) 80, (c) 330, (d) 1000, (e) 5000, and (f) 15000 lx. Solid circles denote dark conditions; open circles indicate overcast.

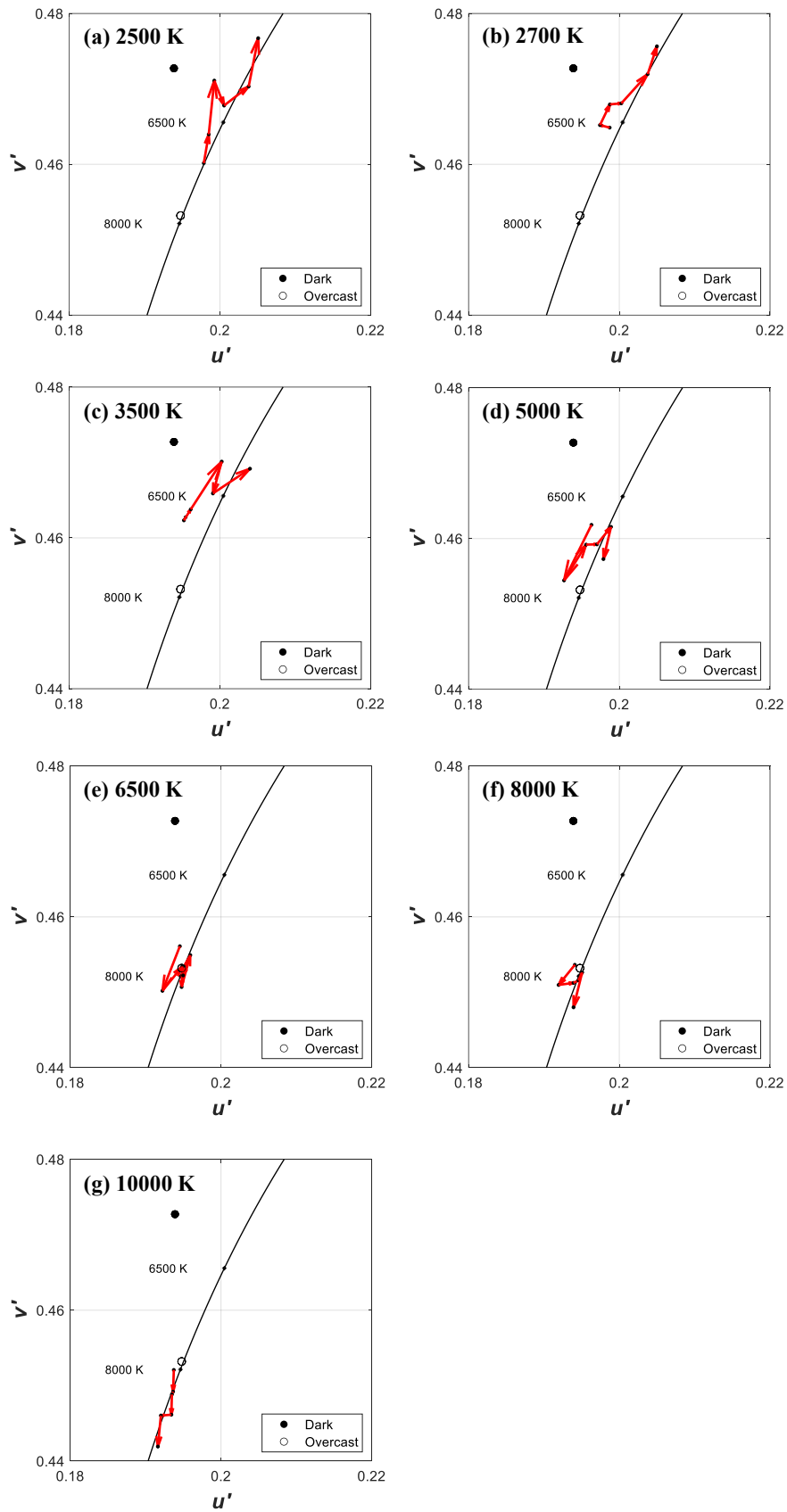


Figure 5-7 Average chromaticities at constant adapting CCT but varying illuminance , showing white point shifts (red vectors) in the CIE 1976 $u'v'$ chromaticity diagram. Conditions: (a) 2500, (b) 2700, (c) 3500, (d) 5000, (e) 6500, (f) 8000, and (h) 10000 K. Solid circles denote dark conditions; open circles indicate overcast.

5.2.3 White point CCT

A look-up table (LUT) of the white point CCTs under different adapting conditions was derived from all the results using the following calculation method. First, the reciprocals of the CCT values for all results were computed. The reciprocal of the CCT was chosen because small intervals in the reciprocal of CCT represent approximately constant quantities independent of the actual CCT [86]. Next, the average reciprocals were calculated for each adapting condition and used to generate the initial LUT, presented in Table 5-4.

Table 5-4 Initial LUT of the white point CCT. The white point CCT is 6477 K under the dark condition, and 7876 K under the overcast condition.

White point CCT (K)		Adapting CCT (K)					
		2500	2700	3500	5000	6500	10000
Adapting illuminance (lx)	30	7021	6634	7035	7045	7638	7906
	80	6741	6691	7046	7926	8394	8346
	330	6238	6447	6903	7291	7846	8142
	1000	6333	6329	6234	7163	8118	8048
	5000	5964	5912	6541	6860	7602	7892
	15000	5573	5646	6003	7257	7954	8478

Under the dark condition, the white point CCT is 6477 K, which is close to D65. Under the overcast condition, the white point CCT is 7876 K, which is close to the white point CCTs of 7602 and 7954 K observed under the conditions of 6500 K with 5000 lx and 6500 K with 15000 lx, respectively.

Both the dark and overcast conditions have unique adapting illuminance values compared to other conditions; therefore, their results were excluded from further analysis. Aiming to provide a practical engineering solution for product application, part of the reciprocal CCTs in Table 5-4 were revised through linear interpolation, with the results provided in Table 5-5. This linear interpolation assumed that the white point CCT consistently approached the adapting CCT as illuminance increased and varied monotonically with adapting CCT at a fixed illuminance.

The fitting error, calculated as the difference in reciprocal CCT ($\Delta(1/\text{CCT})$) between the two LUTs, is shown in Figure 5-8. The results indicate that only a few points require adjustments. These adjustments

were minimal, with the largest occurring at 80 lx and 5000 K, corresponding to a $\Delta u'v'$ of approximately 0.008.

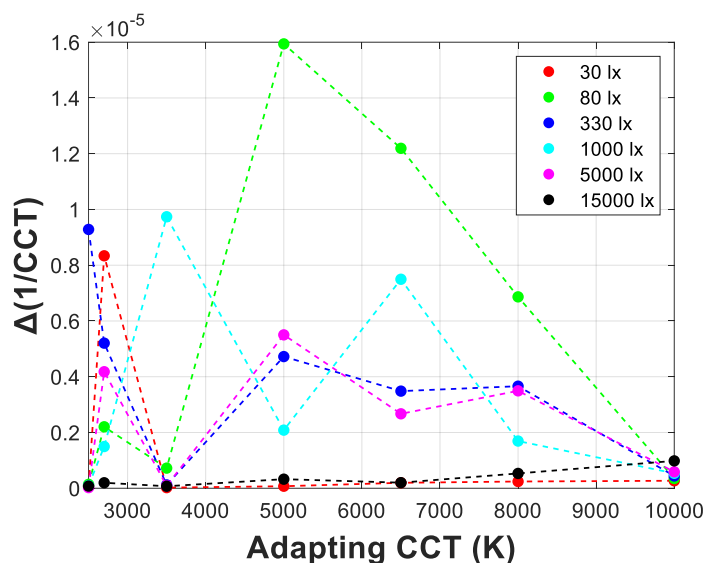


Figure 5-8 Fitting error of the two LUTs expressed as $\Delta(1/CCT)$.

As reported in Section 5.2.2, the intra-observer variability was small, indicating stable observer reliability. Moreover, the display was carefully calibrated, and all adjusted chromaticities were measured after the experiment to ensure measurement accuracy. The average inter-observer variability was approximately 0.010, which exceeded the largest chromaticity shift (about 0.008) introduced in the revised LUT. These results suggest that the fluctuations observed in the original LUT are primarily attributable to inter-observer variability.

Table 5-5 Revised LUT of the white point CCT. The white point CCT is 6477 K under the dark condition, and 7876 K under the overcast condition.

White point CCT (K)		Adapting CCT (K)					
		2500	2700	3500	5000	6500	10000
Adapting illuminance (lx)	30	7021	7024	7035	7045	7638	8067
	80	6741	6794	7013	7046	7639	8377
	330	6625	6679	6903	7050	7645	8453
	1000	6333	6392	6641	7063	7665	8735
	5000	5964	6071	6541	7133	7768	8899
	15000	5573	5646	6003	7257	7954	9488

The data in Table 5-5 were applied to implement the adaptive CCT feature on the smartphone, and their practical applicability was evaluated in Experiment II. The procedure for using the LUT during image processing is illustrated in Figure 5-9.

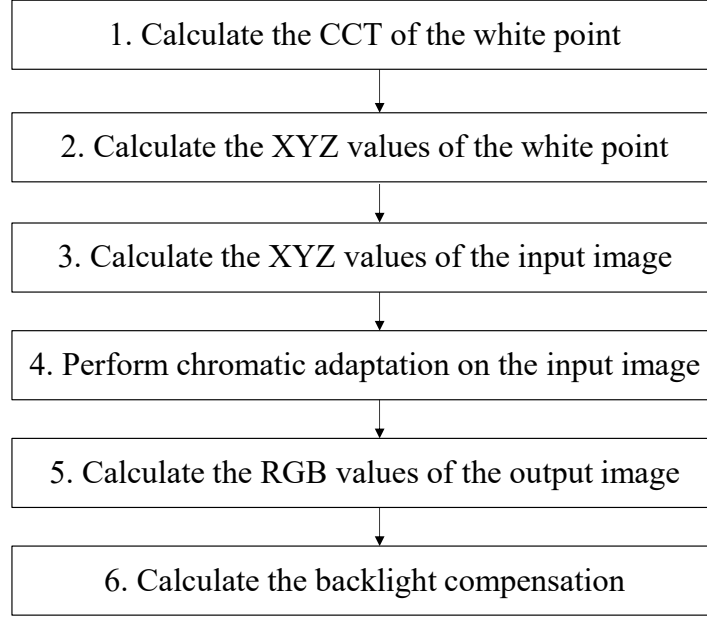


Figure 5-9 Application method of the LUT.

First, the white point CCT was determined by interpolating the reciprocals of CCTs in the LUT based on the sensor-detected ambient illuminance and CCT. Then, the XYZ values were calculated based on the chromaticities of the white point CCT located on the blackbody locus. Note that the Y value of the white point should be scaled to 1.

Thirdly, the XYZ values of the input image were calculated from its linear RGB values using D65 as the reference white point (with sRGB as an example), as shown in Equations (5-3) and (5-4).

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix}_{Input} = \mathbf{M}_{sRGBtoXYZ} \begin{bmatrix} R \\ G \\ B \end{bmatrix}_{Input} \quad (5-3)$$

$$\mathbf{M}_{sRGBtoXYZ} = \begin{bmatrix} 0.4124 & 0.3576 & 0.1805 \\ 0.2126 & 0.7151 & 0.0721 \\ 0.0193 & 0.1192 & 0.9505 \end{bmatrix} \quad (5-4)$$

Fourthly, chromatic adaptation was performed on the XYZ values of the input image according to Equations (5-5) to (5-8). The observer was assumed to be initially adapted to D75, which is widely

used as an adapting white point in industry.

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix}_{Output} = \mathbf{M}_{CAT02}^{-1} \begin{bmatrix} \frac{L_{WP}}{0.9265} & 0 & 0 \\ 0 & \frac{M_{WP}}{1.0368} & 0 \\ 0 & 0 & \frac{S_{WP}}{1.2218} \end{bmatrix} \mathbf{M}_{CAT02} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}_{Input} \quad (5-5)$$

where

$$\mathbf{M}_{CAT02} = \begin{bmatrix} 0.7328 & 0.4296 & -0.1624 \\ -0.7036 & 1.6975 & 0.0061 \\ 0.0030 & 0.0136 & 0.9834 \end{bmatrix} \quad (5-6)$$

$$\mathbf{M}_{CAT02}^{-1} = \begin{bmatrix} 1.0961 & -0.2789 & 0.1827 \\ 0.4544 & 0.4735 & 0.0721 \\ -0.0096 & -0.0057 & 1.0153 \end{bmatrix} \quad (5-7)$$

$$\begin{bmatrix} L_{WP} \\ M_{WP} \\ S_{WP} \end{bmatrix} = \mathbf{M}_{CAT02} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}_{WP} \quad (5-8)$$

Then, the output linear RGB values of the image (sRGB is used as an example) were calculated using Equations (5-9) and (5-10).

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix}_{Output} = \mathbf{M}_{sRGBtoXYZ}^{-1} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}_{Output} \quad (5-9)$$

$$\mathbf{M}_{sRGBtoXYZ}^{-1} = \begin{bmatrix} 3.2410 & -1.5374 & -0.4986 \\ -0.9692 & 1.8760 & 0.0416 \\ 0.0556 & -0.2040 & 1.0570 \end{bmatrix} \quad (5-10)$$

Finally, the backlight compensation level was determined as the maximum RGB value of the white point, as shown in Equations (5-11) and (5-12).

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix}_{WP} = \mathbf{M}_{sRGBtoXYZ}^{-1} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}_{WP} \quad (5-11)$$

$$Backlight \text{ compensation level} = \max \left(\begin{bmatrix} R \\ G \\ B \end{bmatrix}_{WP} \right) \quad (5-12)$$

5.3 Experiment II: magnitude estimation of appearance attributes

5.3.1 Method

Experiment II was conducted to evaluate the practical applicability of the results presented in Table 5-5. The method of magnitude estimation was employed to compare the color appearance of displays using different adaptive CCT solutions. Three smartphones were selected for comparison, including an iPhone 12, a vivo smartphone incorporating the proposed adaptive CCT solution, and a vivo smartphone using the existing solution. To manage observer workload, eighteen adapting conditions from Experiment I were selected for Experiment II. These conditions included the dark and overcast conditions, as well as conditions with CCTs ranging from 2700 to 8000 K and illuminance levels from 30 to 15000 lx.

Prior to the experiment, the stability of the smartphone sensor implementing the proposed solution was tested to ensure that the target white point CCT could be accurately maintained throughout the experiment. Under each adapting condition, the sensed CCT values were recorded over a 30-second period. The minimum and maximum CCTs sensed during this period were used to calculate the actual white point CCT range. These were then compared to the target white point CCTs, which were computed based on the corresponding adapting conditions. The average color differences between the minimum/maximum actual white point CCTs and the target white point CCTs were 0.0004 and 0.0003, respectively, in CIE 1976 $u'v'$ units.

The same viewing booth, viewing table, and LED lighting device used in Experiment I were also employed in Experiment II to ensure consistency of the experimental environment. The three smartphones, an iPhone 12, a vivo smartphone implementing the proposed adaptive CCT solution (referred to as our solution), and a vivo smartphone equipped with the existing adaptive CCT solution (referred to as the existing solution), were placed vertically and side by side on the 45° angled viewing table. Figure 5-10 shows the experiment setup.

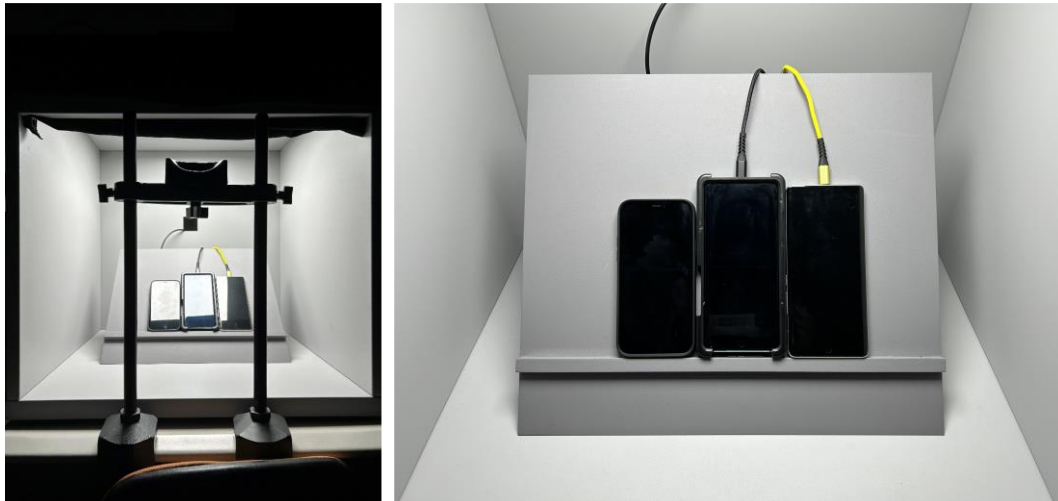


Figure 5-10 Setup of the comparative experiment.

This experiment included eighteen adapting conditions previously used in Experiment I, comprising sixteen conditions arranged in a 4×4 factorial design, one dark condition, and an additional condition simulating overcast ambient illumination (i.e., 6500 K and 12000 lx). Specifically, the sixteen conditions consisted of four illuminance levels (30, 330, 1000, and 15000 lx) crossed with four CCT levels (2700, 3500, 6500, and 8000 K). Figure 5-11 shows all adapting conditions except the dark condition. During the experiment, the auto-brightness and the adaptive CCT feature (True Tone) of the iPhone 12 were turned on to adjust the brightness and color automatically. For the smartphone with the existing solution, the adaptive CCT feature was enabled, while the auto-brightness function was disabled to allow direct control of display illuminance via externally sent auto-brightness signals. In our solution, both the auto-brightness and adaptive CCT features were disabled, as display brightness and chromaticity were adjusted by sending predefined signals based on the results of Experiment I. The auto-brightness signals were identified to its auto-brightness feature, whereas the adaptive CCT signals were calculated according to the LUT derived from Experiment I. Prior to the magnitude estimation task, the display brightness of the iPhone 12 was manually adjusted by the observer to match the perceived brightness of the smartphone using our solution.

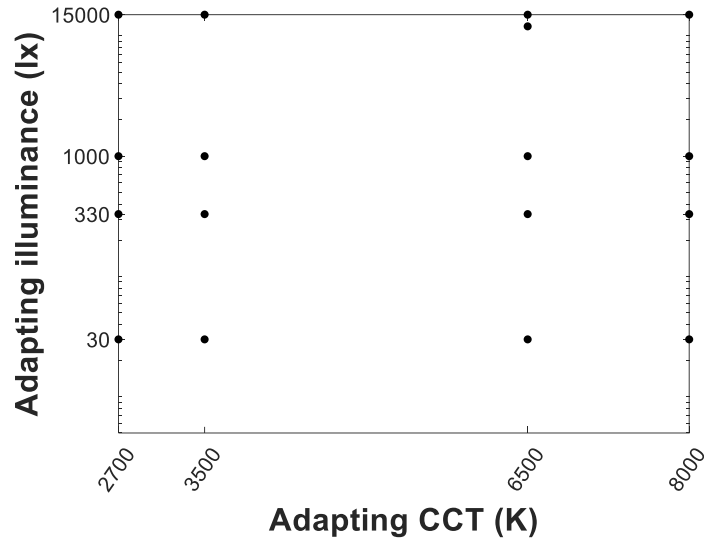


Figure 5-11 All adapting conditions in the comparative experiment except the dark condition.

Six images with varying content were selected for the magnitude estimation task, as shown in Figure 5-12. The selected content categories included a webpage, an icon, a blue image, a green image, a food image, and a skin image. A ten-point scale (ranging from 1 to 10) was used to evaluate each image along four semantic attributes: whiteness (1 for black and 10 for the whitest), comfort (1 for uncomfortable and 10 for the most comfortable), naturalness (1 for fake and 10 for the most natural), and preference (1 for not preferred and 10 for the most preferred). To assist observers during the evaluation, a gray sheet displaying the attribute scales was placed in front of the viewing table. The details of the scale are presented in Table 5-6. It is noted that the preference scores for the webpage and icon images were not collected, due to their large white backgrounds.

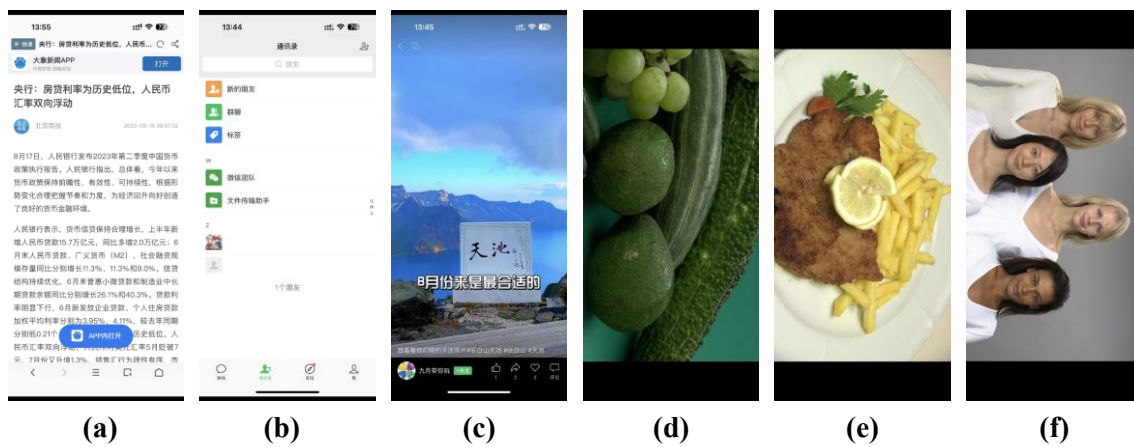


Figure 5-12 All images used for evaluation. (a) Webpage, (b) icon, (c) blue, (d) green, (e) food, and (f) skin image.

Twenty-five observers (twenty males and five females) participated in Experiment II. They all had normal color vision and are between 20 and 30 years of age (mean = 24.0, SD = 2.92). All displays were pre-warmed for 30 minutes prior to the experiment to ensure stable performance. As in Experiment I, each observer was first informed of the experimental procedure and tested using the Ishihara plates. Following this, the observer was asked to adapt to the ambient lighting within the viewing booth for 90 seconds (extended to 2 minutes for the dark condition).

During this chromatic adaptation period, observers placed their chin on a chinrest, and the display remained black. The LED device provided the only illumination during the experiment. After the chromatic adaptation, the first image, webpage image, was displayed in full screen on the smartphone. The observer was instructed to evaluate the appearance of the image on each display without time constraints.

The experimenter recorded semantic ratings reported orally by observers. The next image was displayed once the observer completed the evaluation of all attributes and all displays. The adapting condition switched to the next condition when the sixth image had been evaluated. The same procedure was repeated for all adapting conditions. All adaptation conditions were divided into five groups and ordered from small to large according to the illuminance level. The sequence of conditions within each group was randomized.

Table 5-6 Ten-point scale (from 1 to 10) of semantic attributes. Four semantic attributes are whiteness (1 for black and 10 for the whitest), comfort (1 for uncomfortable and 10 for the most comfortable), naturalness (1 for fake and 10 for the most natural), and preference (1 for not preferred and 10 for the most preferred).

1	2	3	4	5	6	7	8	9	10
Black				Whiteness					The whitest
Uncomfortable				Comfort				The most comfortable	
Fake				Naturalness				The most natural	
Not preferred				Preference				The most preferred	

5.3.2 Results

The inter-observer variations were characterized by the Standardized Residual Sum of Squares (STRESS) [87], as defined in Equations (5-13) and (5-14). STRESS values range from 0 to 100, with low values indicating smaller variations across observers. For example, a STRESS value of 30 means

30% level of disagreement across observers.

$$STRESS = 100 \left(\frac{\sum_{i=1}^n (E_i - FV_i)^2}{\sum_{i=1}^n F^2 V_i^2} \right)^{\frac{1}{2}} \quad (5-13)$$

where

$$F = \frac{\sum_{i=1}^n E_i^2}{\sum_{i=1}^n E_i V_i} \quad (5-14)$$

The E_i values were the average semantic ratings across all observers (i.e., an average observer), while the V_i values were the semantic ratings rated by each observer under adapting condition i . The inter-observer STRESS values ranged from 12% to 23%, with an average of 16%. All inter-observer STRESS values for each adapting condition are summarized in Table 5-7 and are comparable to those in previous studies [88, 89].

Table 5-7 Inter-observer variations of each adapting condition in Experiment II. The inter-observer variations were characterized by the Standardized Residual Sum of Squares (STRESS).

Adapting luminance (lx)	Adapting CCT (K)			
	2700	3500	6500	8000
Dark			23%	
30	16%	17%	16%	17%
330	18%	19%	18%	17%
1000	12%	14%	12%	14%
12000	N/A	N/A	12%	N/A
15000	15%	15%	14%	15%

5.3.2 Semantic rating

Figure 5-13 presents the overall semantic ratings of each solution. The results indicate that our solution outperformed both the existing solution and the iPhone 12. Four average ratings of our solution were all higher than those of the other two solutions, with the most significant improvement observed in whiteness. In terms of median ratings, our solution had higher ratings than those of the other two solutions in whiteness and preference and the same ratings in comfort and naturalness. Moreover, our

solution had smaller box lengths and shorter whiskers regardless of the semantic attributes, which means that the ratings of our solution had higher stability. In contrast, the existing solution had larger box lengths and longer whiskers, suggesting that the ratings of the existing solution had a wider distribution which represents a greater volatility or instability.

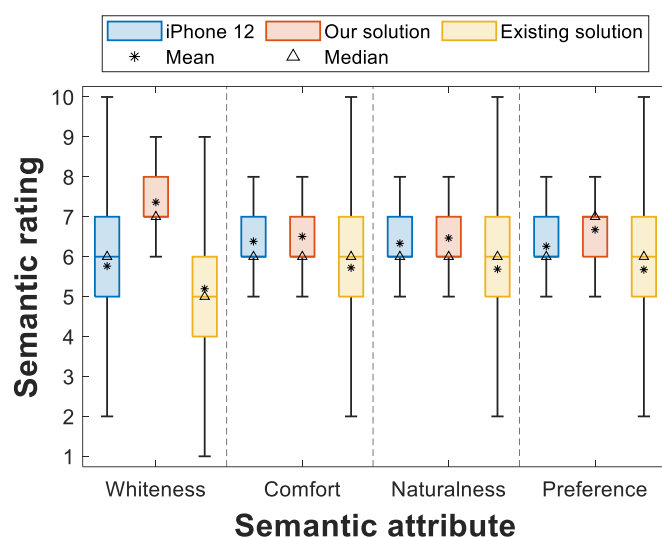


Figure 5-13 Overall results of semantic ratings.

Figure 5-14 shows the semantic ratings of each solution under adapting conditions with the same illuminance or CCT. Our solution was significantly better than the other two solutions in whiteness ratings, especially under the lower illuminance (e.g., 30 lx). For comfort, naturalness, and preference rating, the ratings for our solution were comparable to or slightly higher than those of the iPhone 12, and consistently outperformed those of the existing solution.

Among these attributes, whiteness is an essential attribute that reflects the white appearance of the display under different adaptation conditions. The joint effect of adapting illuminance and CCT on perceived whiteness is illustrated in Figure 5-15. Our solution demonstrated excellent performance under conditions involving both low CCT (2700 and 3500 K) and low illuminance (30 and 330 lx), which are representative of typical indoor environments.

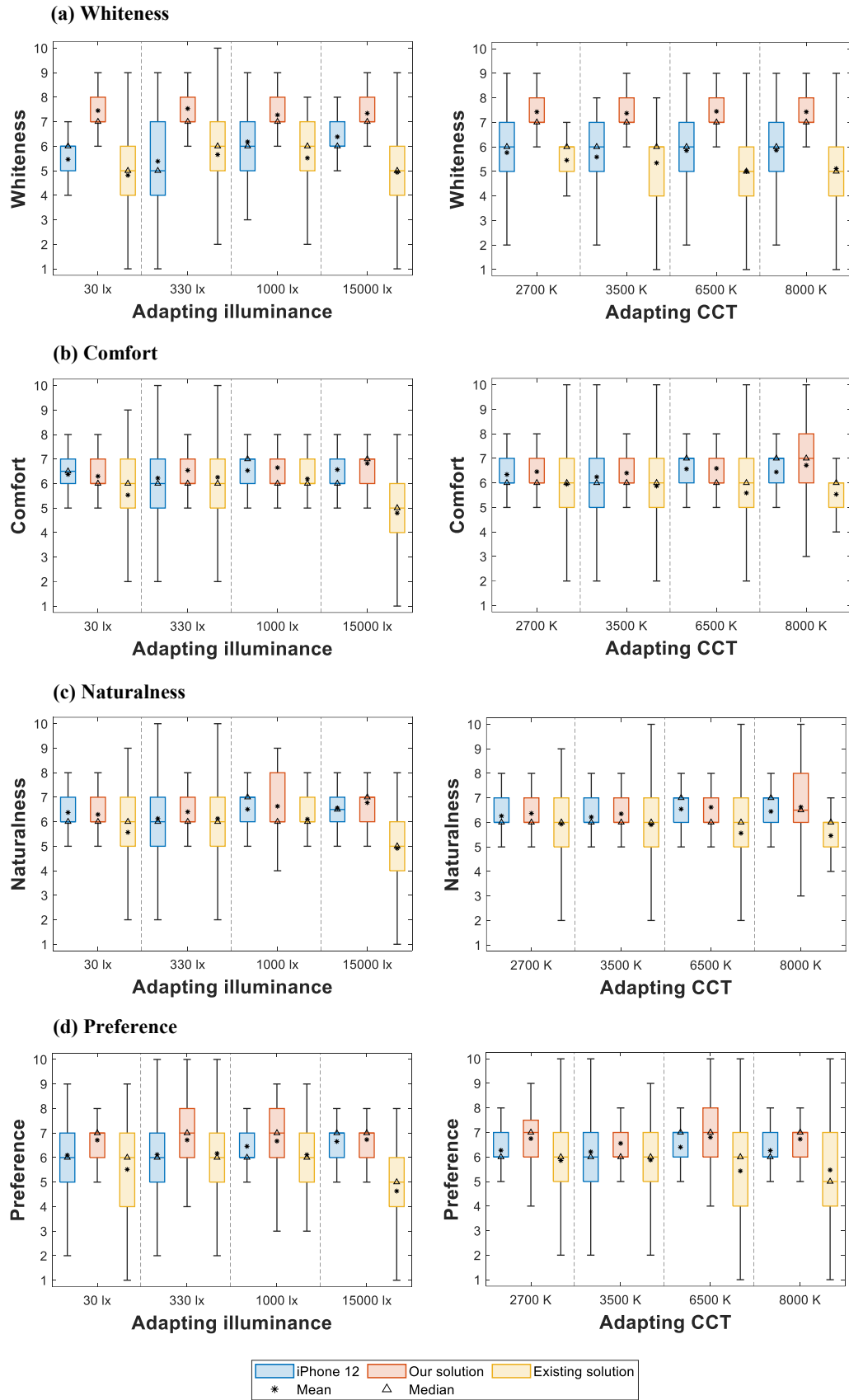


Figure 5-14 Results of (a) whiteness, (b) comfort, (c) naturalness, and (d) preference ratings under adapting conditions with the same illuminance or CCT.

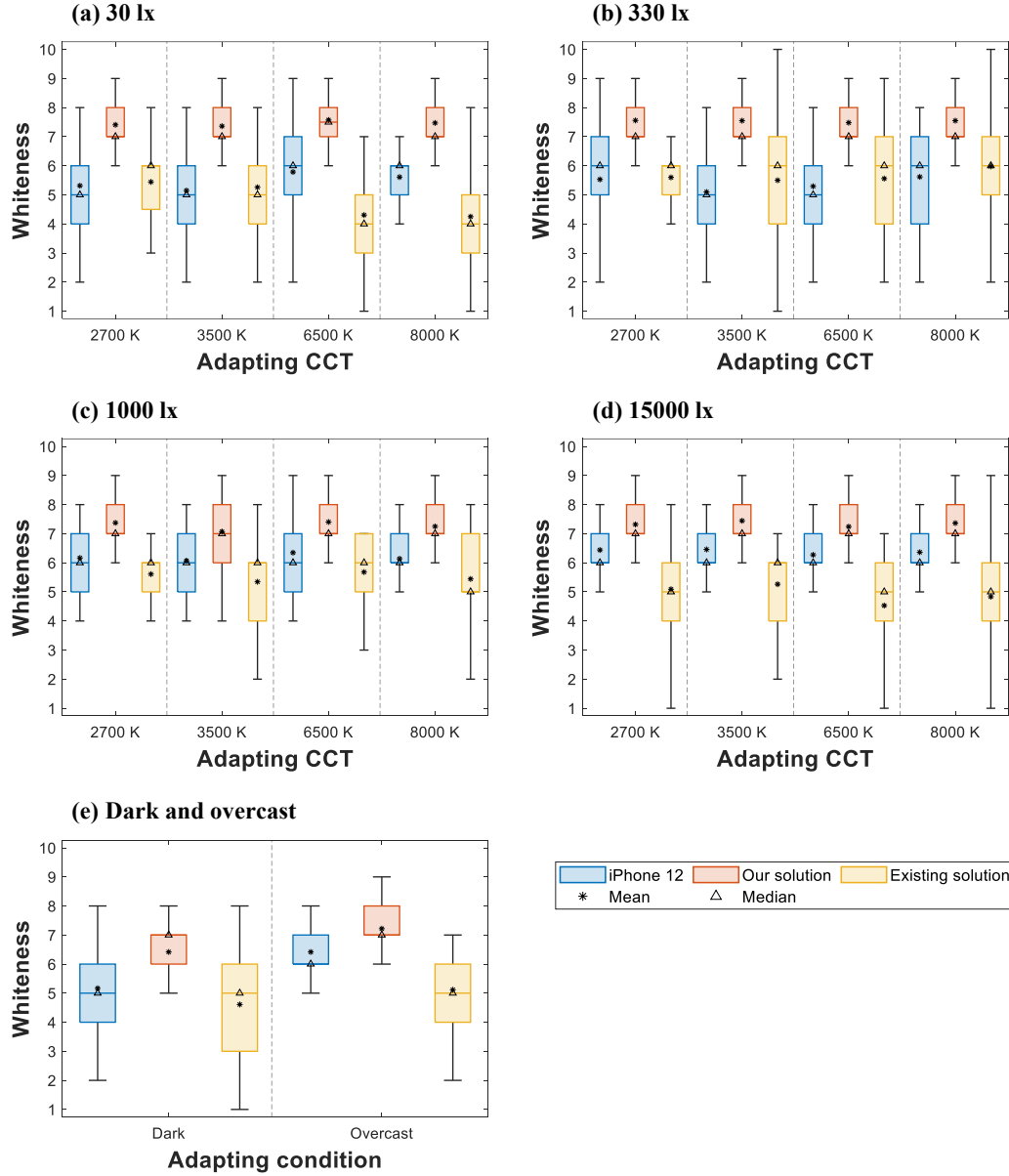


Figure 5-15 Results of the whiteness rating under each adapting condition.

The correlations among the semantic attributes were analyzed and are summarized in Table 5-8. Overall, the evaluations of whiteness, comfort, naturalness, and preference exhibited positive correlations with one another. This is consistent with Figure 5-13, where the mean ratings for comfort, naturalness, and preference are very similar across the existing solution, iPhone 12, and our solution, reflecting their strong correlations.

The strongest correlation was observed between preference and naturalness, indicating that images perceived as more natural were also more likely to be preferred. In contrast, the correlation between whiteness and naturalness was comparatively weak. Additionally, the influence of image category on

the correlations among semantic attributes was examined, as presented in Table 5-9.

Table 5-8 Overall correlations between semantic attributes. All p -values of correlations were less than 0.001.

Spearman ρ	Whiteness	Comfort	Naturalness	Preference
Whiteness	N/A	N/A	N/A	N/A
Comfort	0.578	N/A	N/A	N/A
Naturalness	0.539	0.736	N/A	N/A
Preference	0.570	0.706	0.738	N/A

Table 5-9 Correlations between semantic attributes when evaluating different images. All p -values of correlations were less than 0.001.

	Spearman ρ	Whiteness	Comfort	Naturalness	Preference
Images with white backgrounds	Whiteness	N/A	N/A	N/A	N/A
	Comfort	0.507	N/A	N/A	N/A
	Naturalness	0.555	0.749	N/A	N/A
Images with familiar colors	Whiteness	N/A	N/A	N/A	N/A
	Comfort	0.616	N/A	N/A	N/A
	Naturalness	0.533	0.727	N/A	N/A
	Preference	0.565	0.691	0.736	N/A
Image with skin color	Whiteness	N/A	N/A	N/A	N/A
	Comfort	0.611	N/A	N/A	N/A
	Naturalness	0.530	0.737	N/A	N/A
	Preference	0.590	0.750	0.745	N/A

The six images were classified into three categories: the webpage and icon images were grouped as images with white backgrounds; the skin image was categorized as an image containing skin colors; and the remaining images were considered as images with familiar colors. The correlations among semantic attributes were generally the strongest for the skin image, while they tended to be lower for images with white backgrounds. This result suggests that semantic coherence among whiteness, comfort, naturalness, and preference is more pronounced when evaluating images with skin colors, possibly due to human sensitivity to skin appearance.

5.4 Conclusion

The results confirmed that the proposed LUT enhanced perceptual image quality and demonstrated strong applicability in practical scenarios.

This study investigated how the joint effects of adapting and stimulus illuminance influence the perceived white point of displays, with the aim of deepening the understanding of chromatic adaptation under varied viewing conditions. Two experiments were conducted to support this objective. Experiment I employed achromatic matching across forty-four adapting conditions and revealed that the adjusted white point chromaticities were generally distributed with the blackbody locus. Based on these findings, a LUT of CCTs was developed to represent white point shifts across various combinations of adapting CCT and illuminance. This LUT allows for interpolation of appropriate white point CCTs under diverse ambient conditions. The effectiveness of the LUT was validated in Experiment II, which employed magnitude estimation to evaluate perceptual attributes of images displayed on smartphones. The results confirmed that the proposed LUT enhanced perceptual image quality and demonstrated strong applicability in practical scenarios. In particular, the images used for evaluation that contained skin colors exhibited the strongest correlations across semantic attributes such as comfort, naturalness, and preference, suggesting that observers were more sensitive and consistent in their judgments when evaluating skin appearance.

Chapter 6 Measurements and models for human skin color characterization

6.1 Motivation

Skin color is a crucial aspect of human diversity that has significant historical, social, and political implications in our society and cultural traditions. The study of human skin color holds considerable importance in various scientific fields, including color science, computer vision, disease diagnosis, and makeup development. In computer vision, accurate modeling of skin color is essential for reliable human recognition. In dermatology, skin color is a crucial tool for detecting and diagnosing diseases [50]. Additionally, precise representation of skin color assists in developing different skin treatments for cosmetic applications. For example, skin bio-printing technology can be beneficial for treating skin conditions like vitiligo [90]. In summary, the objective characterization of skin color through scientific methods and reliable techniques is critical in technological innovation and application across various disciplines today. It is essential to understand the significance of skin color in these fields and strive for accurate and precise representation, ensuring advancements in technology and treatment improvement.

Measuring and capturing skin color is a challenging task, and many works in color science and computer graphics have focused on this area. The skin is a multi-layered structure with varying chromophores and thicknesses in each layer, which affect the absorption and scattering properties and lead to variations in skin appearance. Moreover, age, gender, and ethnicity also influence skin appearance, further complicating accurate measurement. When characterizing the properties of an object at different wavelengths, the reflectance spectrum, typically measured through a spectrophotometer, is widely considered to be the most accurate representation of the object's ground truth. For instance, a yellow object reflects wavelengths that correspond to the yellow color in the visible spectrum, giving this object its yellow appearance. Although it is feasible to acquire the reflectance spectra of human skin, these spectra do not fully capture the complexity of skin characteristics. This is primarily due to the non-uniform nature of human skin, whereby a small area measurement does not provide an accurate representation of the entire facial surface. Facial images

captured by cameras are commonly used to characterize the geometric and color characteristics of the human face. However, image color data are device-dependent and therefore cannot be directly used as ground truth for skin color characterization.

Modeling skin color is also a significant challenge as it requires a comprehensive understanding of the underlying biological mechanisms and modeling techniques involved. Some models simplify the properties of human skin rather than strictly follow biophysical principles to characterize the human skin. Common simplifications include describing human skin with fewer layers, ignoring some chromophores that are considered to make minor contributions, and regarding the skin as a homogeneous medium. However, introducing additional input parameters can increase model complexity, potentially hindering practical implementation. Modeling methods also involve trade-offs in accuracy and efficiency. Modeling approaches also involve trade-offs between accuracy and efficiency: simpler models may fail to capture the complex behavior of light propagation in skin, resulting in potential errors. Therefore, researchers strive to accurately characterize the structural and optical properties of skin and to develop models that are both computationally efficient and physically realistic.

In summary, many researchers have focused on the accurate measurement and modeling of skin appearance. This chapter aims to provide an overview of the optical mechanisms, measurement techniques, and modeling approaches used in recent years to characterize human skin appearance.

6.2 Spectral reflectance measurement

Measuring facial skin color presents numerous challenges. First, human skin is an uneven, non-uniform surface with a complex multilayer structure. Second, as a translucent tissue, facial skin permits only indirect observation of internal light interactions. Third, skin measurements are influenced by both the instrumentation and the measurement method [91]. This section introduces two commonly used methods for measuring skin spectral reflectance, which provide information such as the distribution of skin chromophores [92]. The skin color perceived by human eyes is initially generated by a source of visible electromagnetic energy and then modulated due to the optical properties of the skin. To accurately characterize these properties, the influence of the light source on the measured

spectral reflectance must be removed. In practice, skin spectral reflectance is defined as the ratio of the spectral radiance reflected from the target surface to that reflected from a perfect diffuse Lambertian reference.

6.2.1 Spectrophotometer measurements

Spectrophotometers (e.g., Konica Minolta CM700d) are commonly used to measure the spectral reflectance of the skin and to obtain biological information. The measurements using the spectrophotometer are not affected by the ambient illumination but require contact with the skin surface, as shown in Figure 6-1(a).

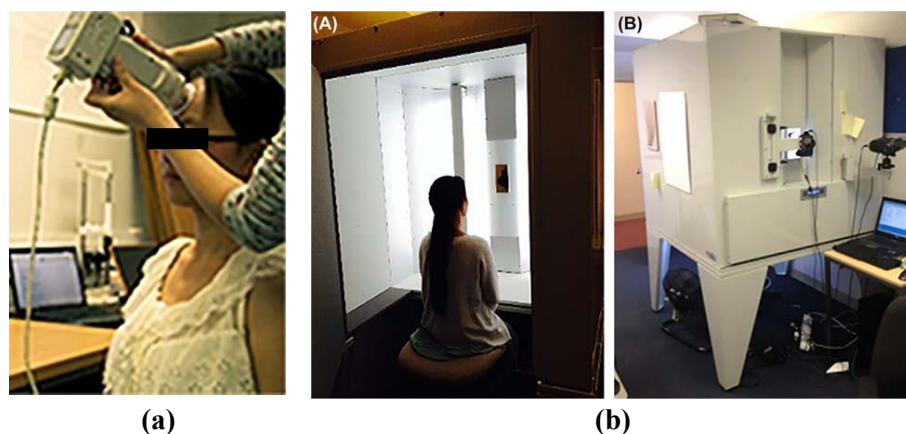


Figure 6-1 Measurement setups of (a) the spectrophotometers and (b) the spectroradiometers, which are established by Wang et al. [91].

The spectrophotometer has a built-in pulsed xenon lamp, enabling measurements including or excluding the specular component. Measurements are conducted with a viewing geometry of CIE recommended $di:8^\circ$ or $de:8^\circ$ (“d” means diffuse illumination, “i” or “e” means specular component included or excluded, and “8°” is the viewing angle), as shown in Figure 6-2. After multiple reflections within the integrating sphere, the skin surface is illuminated with depolarized, uniform light. The detector measures the reflected beam at an 8° angle relative to the skin surface normal. The 8° geometry [72] is widely used because it allows exclusion or inclusion of the specular reflection via a symmetrically placed light trap. White calibration must be performed using accessories after powering on the spectrophotometer and before the first measurement. The accessory used for white calibration is considered a perfect diffuser. The spectral reflectance obtained directly from a spectrophotometer is

the ratio of the spectral radiance reflected by the target surface to that reflected by the perfect diffuser.

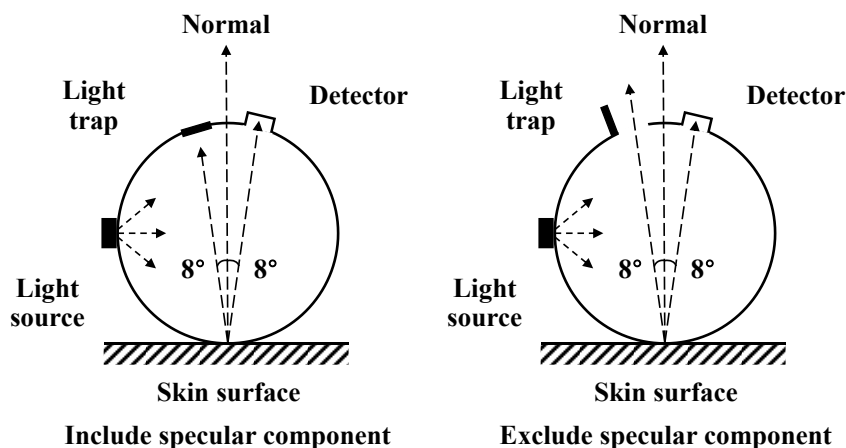


Figure 6-2 Two measurement modes of spectrophotometers, including or excluding the specular component. A light trap is established in instruments to exclude or include the specular component.

6.2.2 Spectroradiometer measurements

The spectroradiometer (e.g., PhotoResearch PR-670 SpectraScan, shown in Figure 6-3(b)) measures the absolute spectral radiance reflected from the target surface under a specific ambient illumination. Therefore, to obtain the spectral reflectance by the spectroradiometer, it is necessary to additionally measure the absolute spectral radiance of the perfect diffuser under the same ambient illumination and geometry condition as the target object. The perfect diffuser is usually approximated by refined barium sulfate or polytetrafluoroethylene (PTFE), as shown in Figure 6-3(c). The spectral power distribution of the light source should be specified and ideally correspond to CIE standard illuminants such as standard illuminants A and D65 [93]. The measurement is conducted in a controlled environment, such as a viewing cabinet painted with a neutral matt color (e.g., Munsell Value N7) [91]. To maintain the geometry condition constant, it is necessary to keep the spectroradiometer stationary during the measurement. Additionally, the diffuser is positioned to align with the target surface. As illustrated in Figure 6-1(b), the spectroradiometer is fixed to the back of the cabinet, with the subject seated inside. Measurement of the different body locations is achieved by adjusting the chair and the sitting position. The viewing cabinet in Figure 6-1(b) is illuminated by a selected light source, a D65 fluorescent simulator. Figure 6-3(a) is a plan view of the viewing cabinet, showing the spectroradiometer aligned along the normal axis (0°) of the subject's skin surface

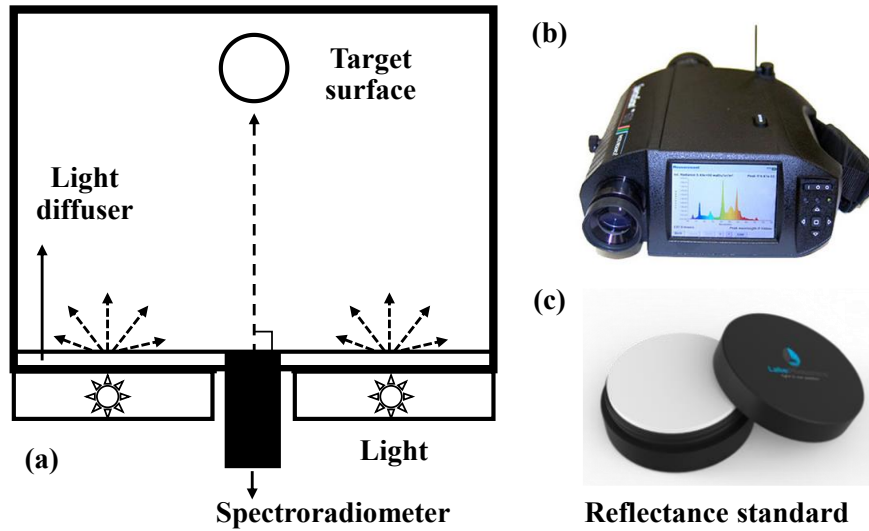


Figure 6-3 (a) Plan view of the viewing cabinet established by Wang et al. [91]. (b) PhotoResearch PR-670 SpectraScan from Jadak Technologies, Inc. (c) Reflectance standard from Lake Photonics GmbH.

6.2.3 Factors impacting measurement

The measurement variabilities of skin spectral reflectance using the spectrophotometer and the spectroradiometer were compared by Wang et al. [91]. They used the CIELAB color difference ΔE_{ab}^* provided by CIE colorimetry [72] as an objectively index to quantify skin color [94]. According to their results, the different measurement distances resulted in a significant color shift for the measurements using spectroradiometers. Their results also show that the aperture size of the target masks and measurement pressure influenced the color shifts in spectrophotometer measurements. Spectrophotometers are more flexible and portable than spectroradiometer and thus are more conducive to collecting skin data of different body locations. For example, Xiao et al. [48] measured skin color data of four different ethnic groups and four different body locations to establish a skin color database using a spectrophotometer.

However, these measurement methods have limitations. Both the spectrophotometer and spectroradiometer can only measure a small area of skin at a time, which does not properly represent the color appearance of the entire face. Therefore, there is a need for a device that covers a wide measurement area to achieve an objective assessment of the color appearance of the human face. In addition, specular and diffuse reflectance of the skin surface cannot be separated completely by using both spectrophotometers and spectroradiometers. Although a light trap is established in

spectrophotometers, the specular component cannot be completely removed, especially when the sample surface is very smooth or highly reflective.

6.3 Spectral reflectance modeling

Capturing images of facial appearance using a digital camera under specific or multiple lighting and viewing conditions has been widely used to collect the skin color for both specific regions [95] and the entire face [96]. In Section 6.3.1, various capturing methods using different setups are introduced with detailed descriptions. Although the camera can comprehensively record the color information of a human face without contact, the color accuracy of images captured by the digital camera depends on the device and the light source. Therefore, the RGB data from captured images must be converted into device-independent to achieve precise color characterization. Numerous studies have been conducted to convert image RGB data to CIE XYZ tristimulus values [96, 97] and to spectral reflectance [36,95] using methods such as polynomial regression, root-polynomial regression, neural networks, and linear transformation matrices. In addition, multiple skin and facial models use biophysical principles as the basic knowledge to estimate spectral reflectance [98]. However, the spectral reflectance estimated by models inevitably deviates from the ground truth, which may significantly impact medical applications that require high precision of color characterization. Therefore, improving the performance of skin models is still a research topic that has received considerable attention. The performance of these models depends mainly on how to describe the optical properties of the skin tissue and simulate the interactions between the skin tissue and light.

The workflow for converting the captured skin images to spectral reflectance is illustrated in Figure 6-4. First, the RAW image data captured by the camera is read. After that, the RGB data is obtained by processing and converting the RAW data from camera RAW space to a color space used for displaying (e.g., sRGB color space). Next, the RGB data is used to derive corresponding skin properties, which have been defined in the proposed skin color models. This step can be done by pre-constructing look-up tables linking RGB values to skin properties and applying neural networks to smooth the data across the entire face [36]. Finally, the output data, spectral reflectance, is calculated using the chosen simulation method according to the skin properties.

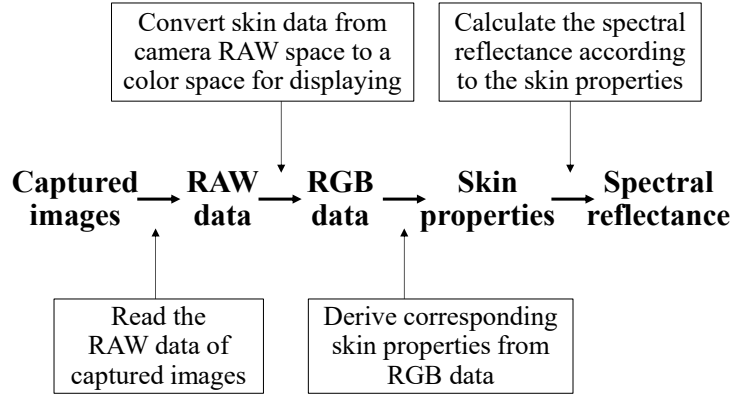


Figure 6-4 Workflow of converting the captured skin images to spectral reflectance.

6.3.1 Setup of capturing systems

Capturing facial images using cameras is a non-contact measurement method that is often used to reconstruct facial color appearance, especially in the field of computer vision. In this field, most of the studies also use the captured data to reconstruct the geometric information of the human face and thus improve the accuracy of the measurement results. To obtain geometric features such as normal maps, multi-angle image capture is required. Image acquisition systems typically consist of multiple cameras, including setups like the light stage [46], face-scanning dome [99], and LED hemisphere [100]. Specifically, the light stage [46] employs a rotating spotlight system that illuminates the subject seated at the center, as shown in Figure 6-5(a).

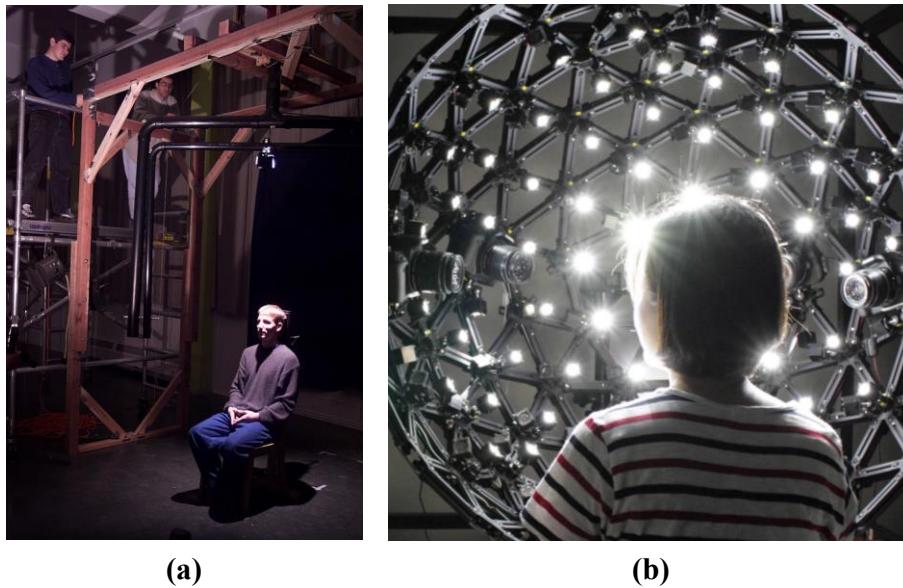


Figure 6-5 (a) Light stage proposed by Debevec et al. [46]. (b) LED hemisphere established in [100].

Furthermore, two digital video cameras are fixed at a distance of approximately 3 meters from the head to capture the left and right sides of the face, respectively. During the acquisition process, the light source of this light stage moves while the subject must remain stationary to ensure complete angular coverage. Systems equipped with multiple cameras and light sources can capture images more rapidly and reduce errors caused by subject movement. For example, Figure 6-5(b) shows a hemisphere device consisting of many light sources and cameras, which is able to provide diffuse illumination and acquire images simultaneously from multiple angles. However, such large-scale systems are structurally complex and expensive. Therefore, recent research aims to develop simpler and more cost-effective solutions. Figure 6-6(a) shows a practical system using 12 DSLR cameras and four flashes without customized hardware. This system applies polarization techniques to capture parallel- or cross-polarized light reflected from the skin, as illustrated in Figure 6-6(b).

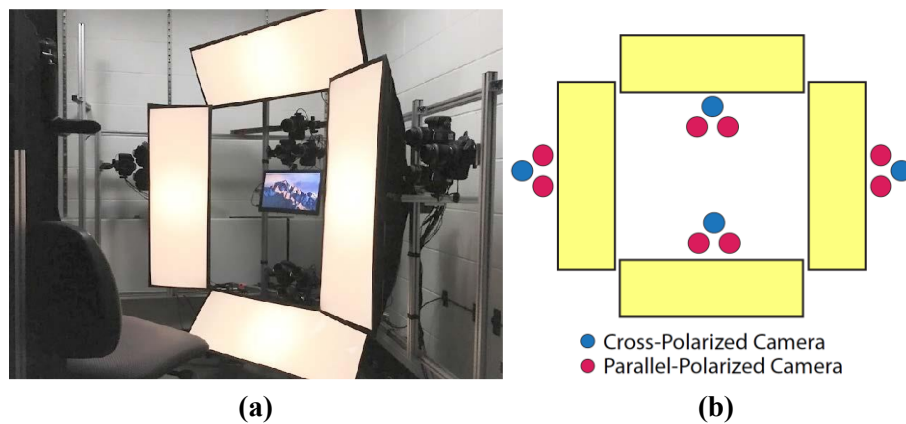


Figure 6-6 (a) Capturing device proposed by Riviere et al. [101] placed linear polarizers in front of the camera and the light source. (b) Horizontal linear polarizers were applied to flashes, and horizontal (parallel-polarized) and vertical (cross-polarized) linear polarizers were applied to cameras.

To sum up, the above studies rely on multi-camera capture systems to acquire facial images under arbitrary viewing directions. However, such systems have inherent limitations. These systems have complex setups and even require custom equipment, hence high costs [101]. Moreover, the introduction of polarization techniques further complicates multi-camera systems, as they require time-consuming and intricate color calibration for each camera. This Chapter focuses on the characterization of skin color instead of the geometrical structure reconstruction of the human face. Therefore, the capturing methods presented in this section are based on the single-camera setup. The human face has textures, hairs, and a three-dimensional structure that creates an uneven surface. Besides, the signal

received by the camera sensor varies from the viewing angle, light source, and state of the skin surface. The capturing setup and measuring details should be clearly described since the signal obtained from a single shot is under a particular setup. Accordingly, this chapter outlines several common and critical capture considerations that must be addressed during data acquisition. Furthermore, separating the diffuse and specular components of skin color images is valuable for both realistic rendering [102] and quantitative analysis of skin color [97]. Diffuse-specular separation is generally achieved using polarization techniques. Therefore, both polarized and non-polarized capture methods are presented. Finally, typical applications of these methods are introduced and discussed.

At present, available standards or technical reports on capturing 3D objects using digital cameras have yet to be found. Therefore, this chapter summarizes key measurement considerations based on relevant CIE technical reports on reflectance measurement [72,93]. First, the captured images should be carefully described and processed. Although some literature does not explicitly state the file format of captured images, this chapter recommends capturing images in RAW format, which showed better and more stable performance than JPG format in analyzing facial skin color in the past study [97]. The images in the RAW format should be appropriately processed, including color characterization and white balance, as described in [66]. It is worth noting that, compared to the commonly used ColorChecker chart, the skin color dataset collected from real human faces has better predictive accuracy in skin color characterization [97].

The geometric condition of capturing is crucial and must be clearly stated when reporting the measurement data. First of all, it is essential to specify the parameters that affect the measurement results, including the incident angle, viewing angle, azimuth angle, the spectral power distribution of the light source, or the wavelength and full width at half maximum of the monochromatic light if a monochromatic light source is used. If the light source is polarized for the separating purpose, the polarization state and the azimuth of the plane of polarization should be specified. The azimuth angle is the angle between the plane of incidence and the plane of view. The camera and the light source are coplanar when the azimuth angle is 0° or 180° . Second, it is vital to ensure that a uniform diffuse illumination is present to prevent shadows or undesired reflections from being captured in images. In order to achieve this, the distance S_1 between the light source and the skin surface should be

approximately equal to the distance $S2$ between the camera and the skin surface, as shown in Figure 6-7.

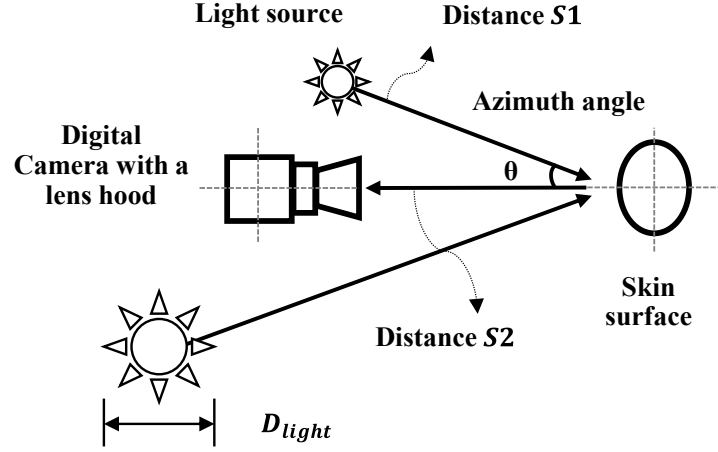


Figure 6-7 Plane sketch of the capturing setup without polarizers.

The camera should be positioned directly in front of the skin surface with an orientation approximately normal to the center of the skin surface. A lens hood is usually placed in front of the camera to block or reduce the light from other angles [97]. In addition, the diameter D_{light} of the emitting area of the light source should satisfy this condition: $D_{light} > (S1 + S2) \times \tan \alpha$, where α is the aperture angle of the camera [93]. Third, the ambient temperature (typically 25 °C) and skin state should be recorded during the measurement. Skin color is affected by the temperature due to the existence of blood. The skin surface should be clean, free from excessive oil, sweat, or other residues, which may interfere with accurate color measurement.

The utilization of polarization techniques can separate the diffuse and specular components and also affect the arrangement of the light source and camera. Figure 6-5 shows the sketch plane of the capturing setup without polarizers. Under this condition, there is no strict requirement for the placement of the light source as long as uniform illumination is achieved. Previous studies applied different values of the azimuth angle between the normal axis of the camera and that of the light source. Some studies used 45° or 60°, while others even did not specify a value. For the condition using polarizers, the light source and the camera should be kept at the same horizontal plane that is the same height. Light is a transverse wave that propagates in a direction perpendicular to its electric and

magnetic fields. Furthermore, the electric and magnetic fields are perpendicular to each other, as shown in Figure 6-8(a). The direction of light polarization generally refers to the direction of the electric field. Figures 6-8(b) and (c) show general setups of the parallel and cross polarization.

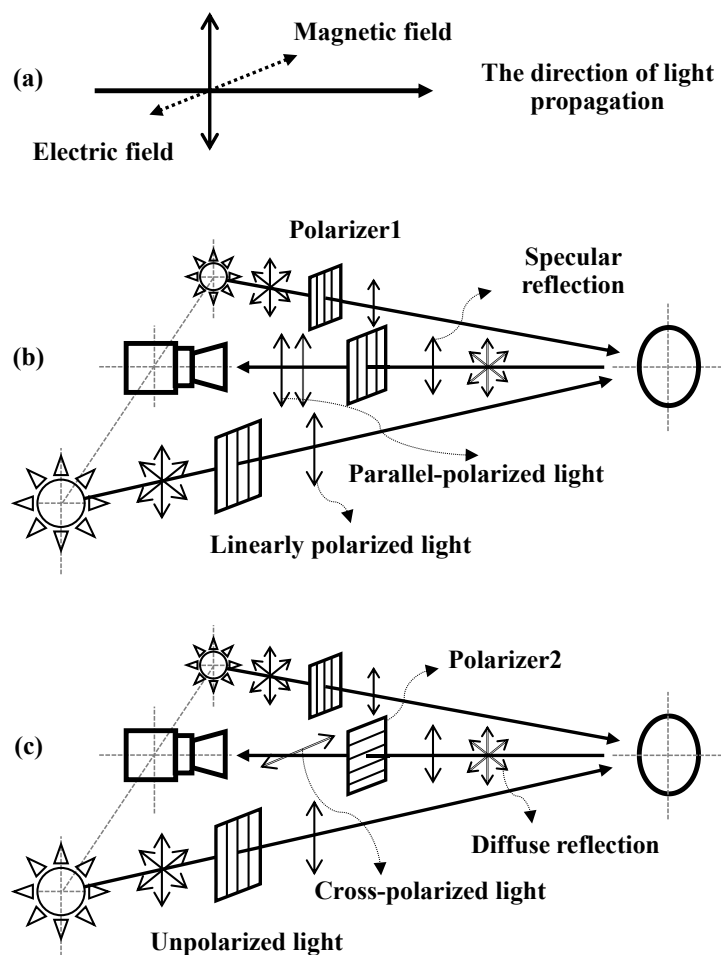


Figure 6-8 (a) Direction of polarization of light. General setups of the (b) parallel polarization and (c) cross polarization.

Note that the setting components shown in Figure 6-7, such as the light source, camera, and skin surface, are omitted in Figures 6-8(b) and (c). The linear polarizer in front of the camera is oriented parallel to that in front of the light source in Figure 6-8(b). The unpolarized light emitted from the light source becomes linearly polarized after passing through the linear polarizer. The specular reflection from the skin maintains its polarization direction, while the diffuse reflection may have different polarization directions. The diffuse reflection can be orthogonally decomposed into two parts: parallel to the polarization direction and perpendicular to the polarizer. Thus, it is assumed that half of the diffuse reflection can pass through the linear polarizer in front of the camera. The specular reflection

is assumed wholly to pass through the polarizer since its polarization direction is parallel to that of the polarizer. In Figure 6-8(c), the polarization direction of the polarizer in front of the camera is perpendicular to that of the polarizers in front of the light source, blocking almost all of the specular reflection and letting approximately half of the diffuse reflection pass. The separating equations, specifically Equations (6-1) through (6-4), are detailed in Section 6.3.2.

6.3.2 Applications of capturing systems

Capturing systems made from readily available consumer hardware and single camera have the benefit of being cost-effective and easy to construct. For example, an image acquisition system consisting of a D65 light source and a Canon digital camera (Canon EOS Kiss X3) was developed by Kikuchi et al. [96] to capture facial color uniformly. Figures 6-9(a) and (b) show this facial imaging system and its plan sketch. This system was designed to evaluate skin color distribution, with an emphasis on color acquisition rather than geometric reconstruction.

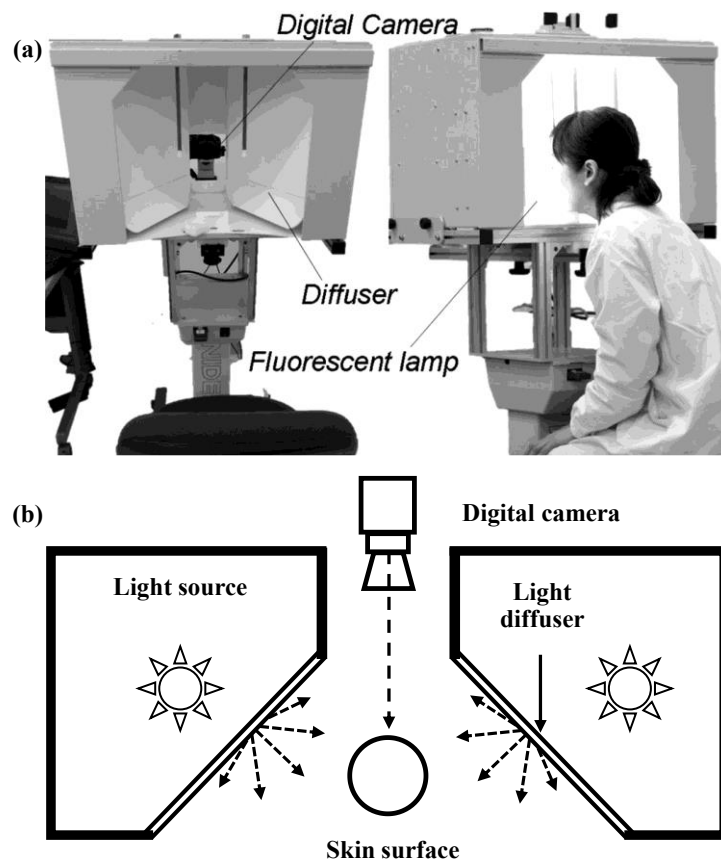


Figure 6-9 (a) Facial imaging system developed by Kikuchi et al. [96] and (b) its plan sketch.

They employed a 3×3 linear matrix to convert RGB values of skin color into CIE XYZ values for analyzing data in CIE $L^*a^*b^*$ color space. The average color differences ΔE_{ab}^* between the skin color measured using the spectrophotometer and the data transformed from RGB data was 2.77, validating the acquisition accuracy of their imaging system and the feasibility of the linear matrix. Apart from using the linear matrix, other methods such as polynomial regression and neural networks can also be employed to transform RGB data into CIE XYZ values [96, 97].

Separating diffuse and specular reflections is a common technique for more detailed analysis of skin color information. The specular component maintains the polarization of the incident light and characterizes the spectral distribution and energy magnitude of the light source. In contrast, the diffuse component reflects the texture and color information of human skin and is depolarized due to scattering interactions. The reflected light from the human skin is impacted by the light distribution and the optical properties of human skin. The polarization state of the reflected light depends on the polarization of the incident light, as well as the geometry, surface texture, and roughness of the skin. To achieve diffuse-specular separation, it is necessary to capture skin images under different polarization states. The introduction of polarization devices in the capturing system is an effective method. Flipping the linear polarizer placed in front of the camera and the light source [102] or placing polarizers with different orientations in front of the camera and the light source [103] can both obtain skin images under different polarization states.

The acquisition system consisting of only one camera and polarizers is enough for diffuse-specular separation [97], as shown in Figure 6-10. With the same acquisition purpose as Kikuchi et al. [96], this system [97] aimed to collect skin color information. In their setup, Xiao et al. [97] placed linear polarizers with mutually perpendicular orientations in front of the camera and the light source. They did not perform the acquisition of images with the parallel polarization state since their goal was to reduce the specular light in the captured images and obtain the diffuse component of the skin reflection.

During facial image acquisition, the skin surface tends to produce highlights that interfere with the measurement. The highlighted area hides the skin color information and affects the measurement accuracy, which will not facilitate the quantitative analysis of the skin color in the captured image.

Therefore, it is critical to minimize specular highlights during the measurement process.

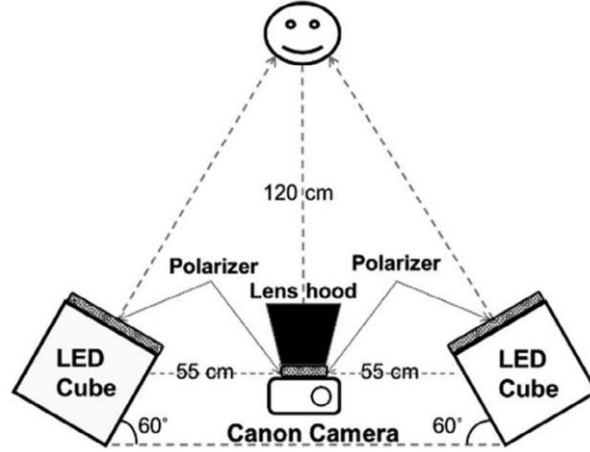


Figure 6-10 Acquisition system with a digital camera and polarizers, as proposed by Xiao et al. [97].

The mathematical procedures for separating the diffuse and specular components from polarized images are detailed in Equations (6-1) through (6-4). Specifically, cross-polarized images contain only half of the diffuse component, as the polarizer in front of the camera blocks all specular light and transmits only the component of diffuse light aligned with its orientation. In contrast, images captured under parallel polarization conditions contain the full specular reflection.

$$I_{cross-polarized} = \frac{1}{2} I_{diffuse} \quad (6-1)$$

$$I_{parallel-polarized} = \frac{1}{2} I_{diffuse} + I_{specular} \quad (6-2)$$

$$I_{diffuse} = 2I_{cross-polarized} \quad (6-3)$$

$$I_{specular} = I_{parallel-polarized} - I_{cross-polarized} \quad (6-4)$$

6.3.3 Simplification of skin structure

Skin structure and molecular components influence the color appearance of the skin, as described in Chapter 2. Skin color models simplify the biological features (e.g., structures and chromophore components) of the skin to varying degrees for different purposes. Some models do not consider the chromophore composition in their modeling, simply assuming that each layer of the skin structure is a homogeneous medium or even treating the skin as a single layer of the semi-infinite medium [36,104].

For example, the study by Jensen et al. [104] did not model the absorption and scattering caused by chromophores but obtained the optical parameters (e.g., reflectance and transmittance) directly from the relevant literature. Although the skin model proposed in [104] achieved better results than models without considering subsurface scattering, the simplification of the skin structure and optical properties resulted in a large gap between the output of this model and the real skin. A commonly used simplified skin structure is a two-layer structure consisting of the epidermis and the dermis [45,105]. In contrast to the model of Jensen et al. [104], the model proposed by Hanrahan and Krueger [45] not only simulated multiple scattering of light but also characterized human skin as a two-layer structure. However, they simplified the two layers to have the same refractive index and ignored the absorption properties of important chromophores within the human skin. Many skin color models tend to overlook and oversimplify the hypodermis and stratum corneum, and solely focus on the epidermis and dermis [105, 106]. Moreover, the dermis is often simplified as a single layer with optical properties equal to the average of the papillary dermis and the reticular dermis [36].

Determining the complexity of a skin model depends on the specific purpose of this model. A complete and detailed skin color model is necessary for medical, dermatological, and cosmetic applications. On the contrary, for applications such as 3D games that demand real-time rendering, the skin color model can be simplified as needed to reduce the complexity of the model by sacrificing accuracy. After determining the skin structure and molecular components of the model, the corresponding biological skin parameters can be obtained according to the related references and equations. It is important to note that different references report different biological parameters. For example, the values of the reduced scattering coefficient fitted by Equation (2-8) varies according to different skin databases, see Table 2-1. In application, Aliaga et al. [36] used the value of reduced scattering coefficients reported by [56] for skin modeling, while a skin aging model [107] was developed by applying skin data from [61].

However, the simulation results obtained by the above models mentioned in this section are inadequate for the current needs of skin color characterization. Also, these results are not precise for describing the interaction of light with human skin. Various methods have been employed to improve the accuracy and flexibility of the skin color model. Increasing the number of structural layers is the most common

approach for optimization that considers the structure [43, 44, 105, 108]. For instance, the BioSpec model [43] was proposed assuming four layers of skin: stratum corneum, epidermis, papillary dermis, and reticular dermis. With consideration of the particle nature and the specific distribution patterns of the melanosomes, Chen et al. [108] proposed a skin model that represents the stratified structure of the epidermis in more detail. Although the model of Chen et al. model is similar to the BioSpec model, they divided the skin structure more complex into six layers, namely stratum corneum, stratum granulosum, stratum spinosum, stratum basale, papillary dermis, and reticular dermis. Models of BioSpec and Chan et al. not only divide the dermis into two layers but also includes the stratum corneum. As the outermost layer of the skin, the stratum corneum significantly influences the skin texture or roughness. However, the contribution of the stratum corneum to the skin color model is controversial. Some researchers hold the perspective that the stratum corneum has almost no effect on skin spectral reflectance due to its small thickness and low absorption [36]. Besides, existing skin color models can barely simulate skin texture based on biophysics, leading to the statement that modeling the stratum corneum cannot contribute much to existing skin models.

Due to the properties of low absorption [56] and high reflectance [109], the hypodermis is often neglected in modeling, which is assumed as a perfect reflector or has a reflectance of 1 [43,108]. Such simplifications lead to an overestimation of absorption in both the dermis and epidermis layers. However, the impact of hypodermis on the skin optical behavior should not be overlooked. Considering hypodermis as a participating layer with 5.9 mm thickness and 1.44 refraction index, the skin aging model proposed by Iglesias-Guitian et al. [107] effectively simulates the skin aging caused by hypodermis. Specifically, their model accounts for a 50% reduction in hypodermal thickness with age, and highlights water loss within the hypodermis as a primary factor contributing to decreased chromophore concentration. This skin aging model [107] completely characterized the skin structure into five layers: the stratum corneum, the epidermis, the papillary dermis, the reticular dermis, and the hypodermis. They stated that simulating hypodermis as a participating layer changed the spectral reflectance of human skin, especially in the range of longer wavelengths.

Although it may not align with biological principles, simulating a virtual skin layer might yield significant benefits. For instance, Donner et al. [105] modeled high absorption that happened between

skin layers by assuming an extremely thin absorption layer between the epidermis and dermis [110] to improve the predictive capabilities of the model. Furthermore, the thickness of each layer is of significant importance for model performance. The thickness of each skin layer varies by gender, age, individual, and body region [40]. It has been proven that the thickness of each skin layer is a critical parameter for skin color models [111], impacting the correct estimation of blood oxygenation.

6.3.4 Simplification of chromophore components

In addition to optimizing the skin structure, many studies have made various assumptions about the spectral distribution of chromophores to improve the skin model performance. Some models have achieved good predictive performance even with a simple two-layer (i.e., epidermis and dermis) structure by finely and accurately characterizing the optical properties of chromophores. The assumption that skin tissue is heterogeneous material can increase the applicability of skin appearance models compared to the assumption that human skin is a homogeneous medium [105]. For instance, Donner et al. [105] considered the effect of absorption caused by melanin, hemoglobin, carotene, and oiliness on the model performance during modeling to achieve a better reproduction of skin color appearance over various skin types and conditions. Other factors such as epidermal roughness, the amount of sebum, collagen density in the dermis, and the thickness of each skin layer also significantly influence skin color appearance [107]. In detail, the rougher the skin becomes, and the lower the amount of sebum, the more aged the skin appears. This is because these changes lead to changes in the optical properties of the skin, which impact skin color appearance. Aging skin is generally characterized by a decreased number of collagen fibers, lower chromophore concentration, and thus appears thinner and drier due to a slower metabolism. In addition, water is generally not considered a factor affecting the appearance of the skin. However, Iglesias-Guitian et al. [107] suggested that water decreases with age, causing the skin to become drier. They indicated that although water is not a highly absorbent component, it has a significant impact on color appearance.

6.3.5 Simulation of light propagation

The simulation of light propagation plays a critical role in establishing the relationship between biophysical properties and spectral reflectance, thereby significantly influencing the performance of

models used to predict skin spectral reflectance. Methods for simulating light propagation in skin tissue are generally classified into deterministic and nondeterministic approaches.

Deterministic methods use formulations based on analytical approximations of radiative transfer equations to model the interaction between light and skin tissue [108], such as Kubelka-Munk (K-M) theory [112] and diffusion theories [106]. As a representative deterministic method, the K-M-based model utilizes scattering and absorption coefficients to describe radiation transmission in a medium. It assumes that the medium has a small inhomogeneity compared to its thickness [113]. Deterministic methods require fewer calculations and get faster results, resulting in better real-time performance in practical applications. However, the effectiveness of these models is limited by the analytical approximations used. The K-M-based model obtains relatively fast results by simplifying the material description and therefore lacks a more detailed analysis of the structural and optical properties of different skin tissues [113]. Models based on diffusion theory are relatively easy to use and are applicable to analyzing data [113]. However, the diffusion approximation method is limited by the optical properties of the medium (e.g., skin tissue). In detail, when the absorption coefficient of a medium is not significantly smaller than the scattering coefficient, diffusion theory cannot accurately describe the light transmission that occurs within that medium [113]. Recently, Aliaga et al. [36] tested the performance of K-M-based models for the reconstruction of skin reflectance and concluded that these models could not reliably recover a sufficiently wide range of skin types. They finally chose the Monte Carlo (MC) method to achieve the goal of reconstructing the optical properties of human skin.

Nondeterministic methods rely on stochastic techniques, most notably the Monte Carlo (MC) method [108], and are often combined with ray optics techniques [103]. The MC method, one of the earliest stochastic techniques for modeling radiation transport [114], has been widely adopted to simulate photon trajectories, which represent the propagation of light through scattering media such as skin. In this context, photon propagation is modeled as a random walk, where photons are probabilistically scattered and absorbed within the tissue. Figure 6-11 describes the simulated process of photon propagation in human skin. A photon is set to move in a random step size after being emitted into the skin tissue. After moving, if this photon hits the boundary, it will be reflected or transmitted; if not, it will be absorbed and scattered. The photon is recorded as reflected light if the transmission occurs at

the outermost boundary that connects with the air. The above process is repeated for each photon until its weight is small to below a predefined threshold. Moreover, it is necessary to use the roulette technique [115] to determine whether the photon will survive. This step can improve the simulation accuracy as it serves as an additional judgment for determining the termination of photon propagation.

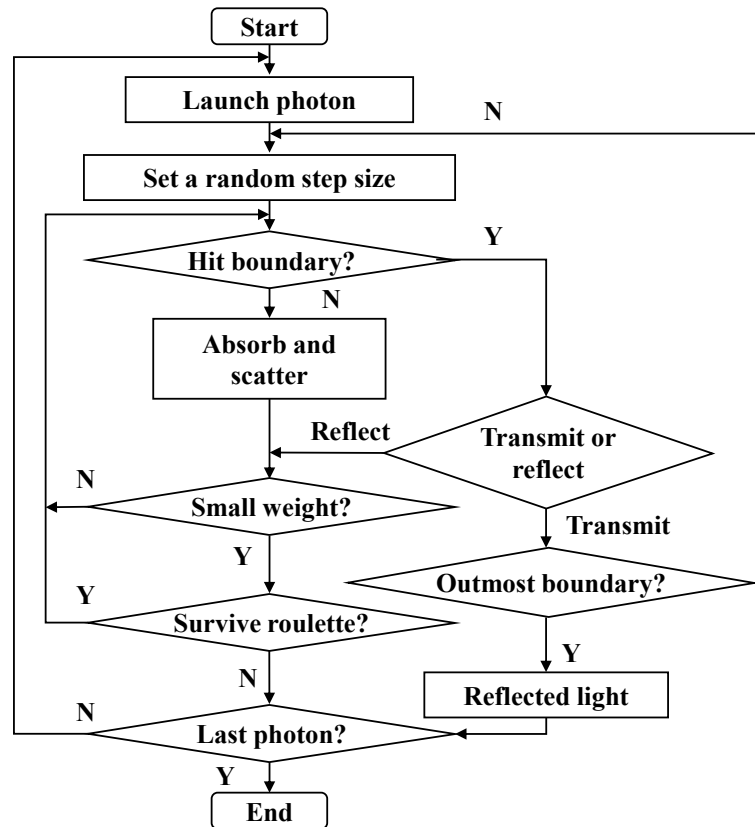


Figure 6-11 Flowchart of photon propagation in human skin, simulated using the Monte Carlo method. “Y” and “N” mean “yes” and “no”, respectively.

The nondeterministic method is applicable to biological tissues with complex structures and optical inhomogeneities [116]. This method simulates the propagation of a large number of photons traveling through the tissue, undergoing reflection, refraction, absorption, and scattering. This type of model can provide high-fidelity results due to its fewer assumptions by being essentially based on fundamental biological and physical mechanisms. The models of Chen et al. [108] and Iglesias-Guitian et al. [107] were extensively evaluated by comparing their predicted values with actual measured data, demonstrating that the results provided by stochastic models of light transmission in skin tissue can be highly predictable. However, the computational cost limits MC-based models, and simulation results often were obtained over a significant amount of time. To address this issue and improve real-time

performance, hardware acceleration and parallel computing strategies are commonly adopted [117, 118]. Furthermore, the use of precomputed look-up tables and the neural networks were confirmed to be useful strategies for achieving efficient computation in Aliaga et al.'s study [36].

6.4 Conclusion

Characterizing human skin color is a crucial research topic that aims to enhance the understanding of the optical properties of human skin and describe better skin color appearance. Accurate measurement and robust modeling are vital in characterizing skin color. This chapter began by discussing the challenging task of measuring the spectral reflectance of human skin. The spectroradiometer measurements were sensitive to measurement distance, with even small variations leading to noticeable color shifts. Spectrophotometer measurements were affected by aperture size and the measurement pressure, both of which introduced variability in the recorded data. Furthermore, neither method can completely separate specular and diffuse reflectance components, which is essential for accurate color characterization. These findings underscore the need for improved measurement systems.

The spectral reflectance measured from a small skin region may not be representative of the entire face, and camera-captured images cannot serve as precise substitutes for spectral data. Subsequently, the chapter reviewed skin reflectance modeling methods. Factors such as the skin's multi-layered structure, the absorption and scattering behavior of various chromophores, complicate the modeling process. Moreover, these skin models must balance efficiency with accuracy. While simplified models may support real-time applications, high-fidelity simulations require detailed structural and biophysical information. With the advancement of measurement technologies and the growth of interdisciplinary research, it is anticipated that future methods will offer enhanced accuracy, reliability, and computational efficiency. This chapter aims to serve as a comprehensive reference for researchers engaged in the study of skin color appearance.

Chapter 7 Skin color characterization through skin scales and models

7.1 Motivation

Skin scales are constructed collections of color samples, specifically designed to facilitate the estimation, classification, evaluation, and measurement of human skin colors. These scales serve as essential reference tools in various applications, ranging from determining sunburn susceptibility to assessing the effectiveness of skin care products. By offering a consistent color reference, skin scales enable more accurate comparisons and analyses of skin colors across different populations and conditions, thereby improving the reliability and validity of both research and practical outcomes. In contrast, skin models are computational or physical simulations that replicate the complex structural and optical characteristics of human skin. These models are developed to simulate how light interacts with various skin layers, including the epidermis and dermis, as well as with chromophores such as melanin, hemoglobin, and other pigments. By modeling processes such as absorption, scattering, and transmission, skin models provide a detailed representation of how skin color appears under varying illumination conditions. In addition to predicting the visual appearance of skin, these models allow for the exploration of how factors such as age, health status, or environmental exposure influence skin color perception. Both skin scales and skin models serve as crucial references for skin color characterization. While skin scales provide a practical means of classifying and evaluating skin tones, skin models offer a more dynamic and flexible approach for investigating the optical and biological mechanisms of skin color.

Accurate prediction and representation of skin color are essential in dermatology, cosmetics, and imaging. Skin models support biomedical research, clinical simulations, and cosmetic science by simulating interactions between light and skin under diverse conditions. Skin scales complement these models by providing standardized metrics for quantifying skin color, texture, and related attributes. Although models based on physical principles have advanced considerably, their integration with empirical skin scales remains limited. This gap highlights the need to combine skin models with skin scales to improve both predictive accuracy and practical applicability. This study aims to address these gaps by integrating skin models with skin scales to establish a more robust and comprehensive

framework for skin color characterization. This study begins with an overview and analysis of representative skin scales, followed by a description of the skin model. Then, a skin model is developed and its predictive performance is evaluated. Finally, based on the proposed model, an experiment is designed to investigate the minimum skin color differences that can be perceived.

7.2 Skin scale and skin model

7.2.1 Basic information of skin scales

Various skin scales have been developed based on different measurement methods, usage purposes, and populations. One of the most widely used is the Fitzpatrick Scale [119] which primarily estimates an individual's sunburn tendency, serving as a critical tool in dermatology and skin care. It categorizes skin types based on their reaction to ultraviolet (UV) exposure, and divides skin types into six categories (from I to VI). Each category reflects different skin tones and levels of sun sensitivity. For example, Type I skin almost always burns and rarely tans when exposed to sunlight, while Type VI skin rarely burns and tans very easily. Classification within this scale is based on a questionnaire in which individuals answer questions about their skin's natural response to sunlight, particularly focusing on factors like how easily they burn or tan.

The Taylor Hyperpigmentation Scale [120] was specifically developed to monitor skin changes affected by hyperpigmentation. It comprises 15 skin hues, each containing 10 progressively darker bands that represent increasing degrees of pigmentation. However, comprehensive RGB data for this scale is not readily available in existing public resources.

Several skin color scales have been developed to classify racial groups across different populations. Among them, the Von Luschan's Chromatic Scale is one of the most widely recognized, consisting of 36 skin tones [121]. These tones are visually matched to an individual's skin to facilitate racial classification. However, because the scale is composed of physical glass tiles, accurately acquiring RGB data is difficult. Although some RGB values have been extracted by scanning the original tiles and applying digital tools, this approach may introduce errors due to variations in lighting and scanning conditions. As a result, RGB values from this scale are not included in this study.

The PERLA Color Palette is another classification tool designed to evaluate skin color, specifically within Latin America, and consists of 11 skin tones derived from Internet photographs [122] (Available online: <https://perla.princeton.edu>). Similarly, the PRODER Color Palette was developed to classify skin color in Mexico, selecting 11 skin tones from the PANTONE SkinTone Guide [123].

The NIS Skin Color Scale, also known as the Massey-Martin Scale, is widely used in studies on racial and ethnic identity. It comprises 11 tones created with the assistance of a graphic designer [124]. In this study, RGB values for the NIS scale were obtained from a dataset collected by Soren Brockdorf, who recorded 48 samples per tone using a digital eyedropper tool [125]. The average RGB values of these samples were used for further analysis.

The Monk Skin Tone Scale, developed by Dr. Ellis Monk [126], is a skin tone classification system designed to improve skin tone evaluation. This scale includes 10 distinct skin tones and is considered more inclusive than the Fitzpatrick Scale [127]. The PANTONE SkinTone Guide is another widely used tool for skin tone classification, offering a reliable reference for matching skin tones in applications such as makeup, skincare, and fashion [128]. The 2023 edition of this guide includes 138 skin tones selected from a broad range of skin measurements obtained using a spectrophotometer.

The L'Oréal Skin Tone Color Scale [129] was developed to support product development and precise color matching across a diverse range of skin tones. This scale comprises 66 skin tones, derived from color measurements of over 1000 women representing various ethnic backgrounds, including individuals of Caucasian, mixed-race, Asian, and African descent [130]. The scale was designed based on the distribution of these measurements within the CIELAB h^*-L^* plane, ensuring comprehensive coverage of skin color variations.

A summary of all scales is presented in Table 7-1, including their names, purposes, references, and number of categories. Scale 1 does not provide color samples or RGB values. For scales 2 and 3, reliable data sources were unavailable, as previously mentioned. Scales 4, 6 and 9 provide images of the scales, from which RGB values were extracted using XnViewMP software. RGB values are openly accessible for scales 5 and 7. RGB values for the PANTONE SkinTone Guide were obtained through membership access.

Table 7-1 Summary of skin scales: names, purposes, references, number of skin tones.

No.	Name	Scale purpose	Reference	Number of skin tones
1	Fitzpatrick Scale	Sunburn tendency estimation	[119]	6
2	Taylor Hyperpigmentation Scale	Hyperpigmentation estimation	[120]	150
3	Von Luschan's Chromatic Scale		[121]	36
4	PERLA Color Palette	Racial classification	[122]	11
5	PRODER Color Palette		[123]	11
6	NIS Skin Color Scale		[124]	10
7	Monk Skin Tone Scale	Skin tone classification	[126]	10
8	PANTONE SkinTone Guide		[128]	138
9	L'Oréal Skin Tone Color Scale	Skin care product evaluation	[129]	66

7.2.2 Analysis of skin scale in CIELAB color space

The RGB values of all accessible skin scale were converted into the CIE XYZ values and subsequently transformed into the CIE LAB values. The original images of the PERLA Color Palette were provided in the Adobe RGB format, all other scales utilized the sRGB format. Figure 7-1 presents the computed L^* , a^* , b^* , C_{ab}^* , and h_{ab} values for all scales. Observations from Figure 7-1 reveal that the NIS scale exhibits distinct differences compared to the other scales.

This is evident in the median L^* value of the NIS skin color scale, which is significantly lower (44.5) than the median L^* values of the other scales (approximately 60). The most notable difference is observed in the distribution of hue angles. The NIS skin color scale includes skin tones with hue angles exceeding 300° , displaying a much broader range of hue angles compared to the other scales. These tones, located in the fourth quadrant of the a^*-b^* plane, correspond to red-blue hues. Such hues deviate substantially from the typical range of human skin tones. Therefore, data from this scale were excluded from subsequent analyses.

The remaining five scales are designed for different regions and populations. Although both the PERLA and the PRODER Color Palette aim to assess respondents' skin tones, their target audiences differ: the PERLA is designed for Latin America, while the PRODER focuses on 25- to 64-year-old residents in private households in Mexico. The Monk Skin Tone Scale is intended to examine skin tone

stratification and colorism in the Americas and potentially beyond. The L'Oréal Skin Tone Color Scale has a much broader scope, aiming to assess the skin color of women from all parts of the world. The PANTONE SkinTone Guide is even more expansive in its vision, seeking to represent the full spectrum of human skin types. Although specific data details are undisclosed, the PANTONE website states their data collection was inclusive and representative of diverse skin tone samples from volunteers worldwide.

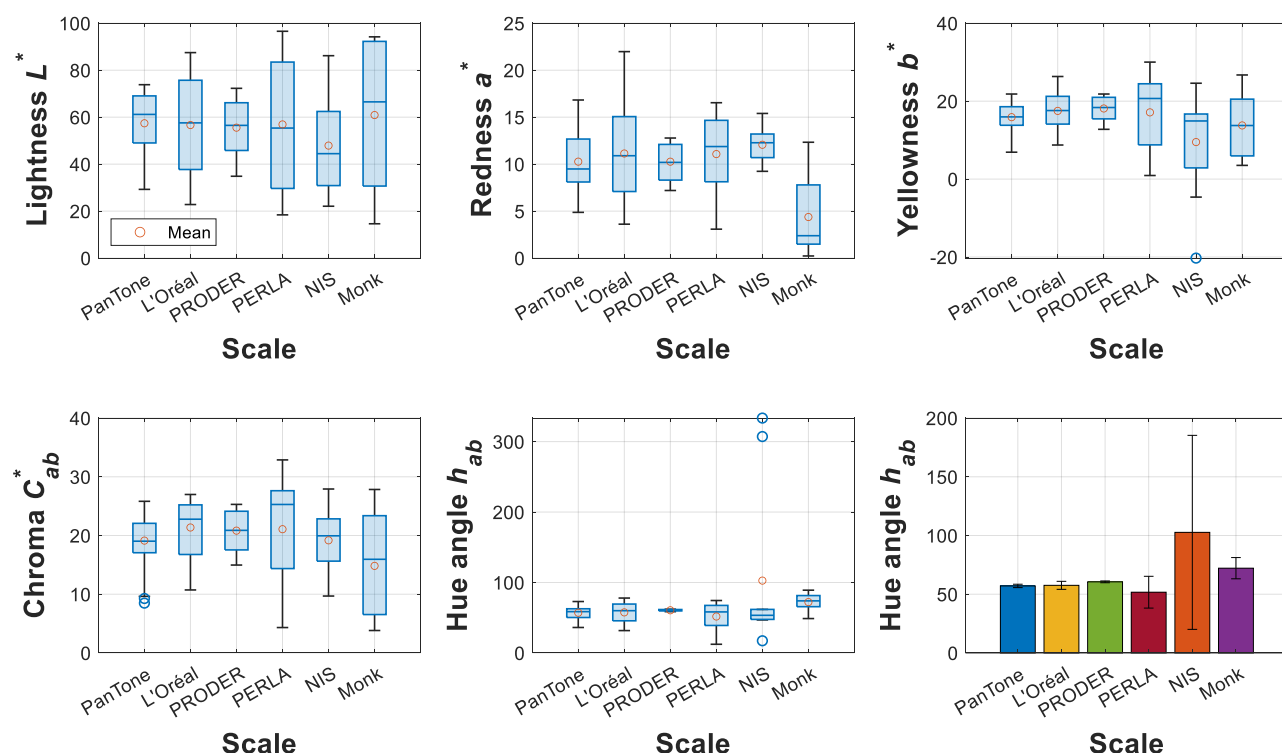


Figure 7-1 Box plots of L^* , a^* , b^* , C_{ab}^* , and h_{ab} values for skin scales. The final subplot presents a bar chart showing the mean h_{ab} values for each scale.

However, the range of CIE LAB values does not always align with the intended coverage of these scales. For instance, the PERLA Color Palette, designed specifically for Latin America, exhibits the largest range across L^* , C_{ab}^* , and h_{ab} among the scales analyzed. In contrast, the PANTONE SkinTone Guide, which aspires to cover the widest spectrum of human skin types, has the smallest L^* range. The PRODER Color Palette shows the narrowest hue angle range (58.6° – 62.1°), reflecting its design: this scale selects 11 colors from the PANTONE SkinTone Guide, all with the same PANTONE hue code (1Y).

Figure 7-2 was created to further analyze the range of skin scales and assess the similarities or

differences between them. It consists of: (a) a 3D plot in the $L^*-a^*-b^*$ space, and projections onto (b) the $C_{ab}^*-L^*$ plane, (c) the a^*-b^* plane, (d) the $h_{ab}-L^*$ plane, and (e) the $h_{ab}-C_{ab}^*$ plane. Figures 7-2(a) and (b) show similar overall distribution patterns of the scales. Specifically, the C_{ab}^* values of skin tones tend to be lower at both low and high L^* values while peaking at mid-range L^* values. The scales exhibit an inverted “C” shape on the $C_{ab}^*-L^*$ plane, which aligns with findings from previous studies [131]. Figure 7-2(c) provides a visual representation of the distribution range and pattern of hue angles across the scales. The L’Oréal scale appears to be uniformly distributed within its range, likely due to its design principle of sampling evenly across the $h_{ab}-L^*$ plane [130], as also evident in Figure 7-2(d). In contrast, Figure 7-2(d) shows that the PANTONE scale displays a non-uniform distribution; its hue angle coverage is narrower at low L^* values compared to higher L^* values. Furthermore, Figure 7-2(c) reveals that most colors in the Monk scale have relatively larger hue angles, resulting in the scale representing overall yellower skin tones. Lastly, in the a^*-b^* plane, several data points from the PERLA scale deviate significantly from the regions covered by other scales.

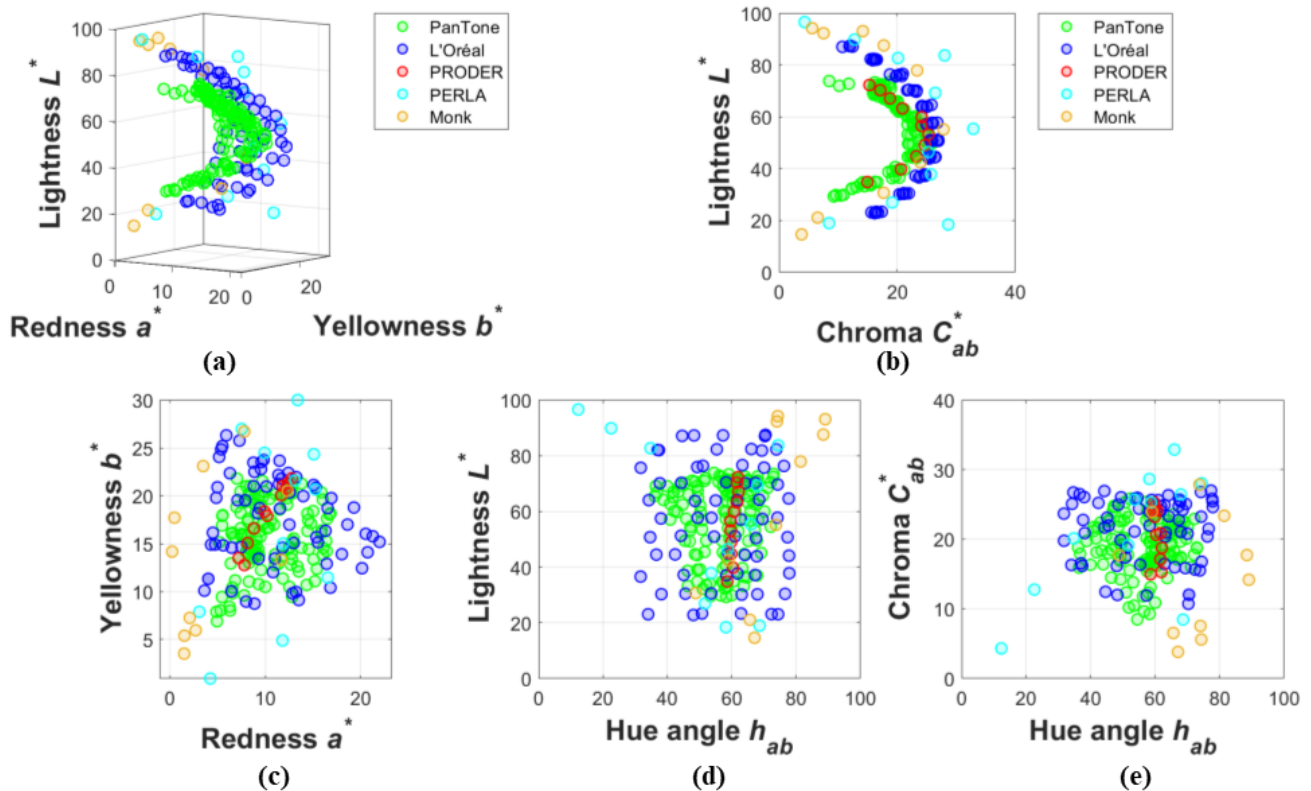


Figure 7-2 Plots of skin scales in the CIELAB color space: (a) a 3D plot in the $L^*-a^*-b^*$ space, and projections onto (b) the $C_{ab}^*-L^*$ plane, (c) the a^*-b^* plane, (d) the $h_{ab}-L^*$ plane, and (e) the $h_{ab}-C_{ab}^*$ plane.

Although the ranges of the scales within the CIELAB color space are similar, the number of colors included in each scale varies, leading to differences in the step size between adjacent colors. This is illustrated in Figure 7-3, which presents 3D visualizations of the distribution of each skin scale in the CIELAB color space. Each color is rendered using its corresponding RGB value and labeled sequentially based on its order within the scale. Black arrows connect the colors in sequence, visually representing their order. For scales with a larger number of colors, such as the PANTONE and L'Oréal scales, the labeling was guided by their respective categorizations or color order.

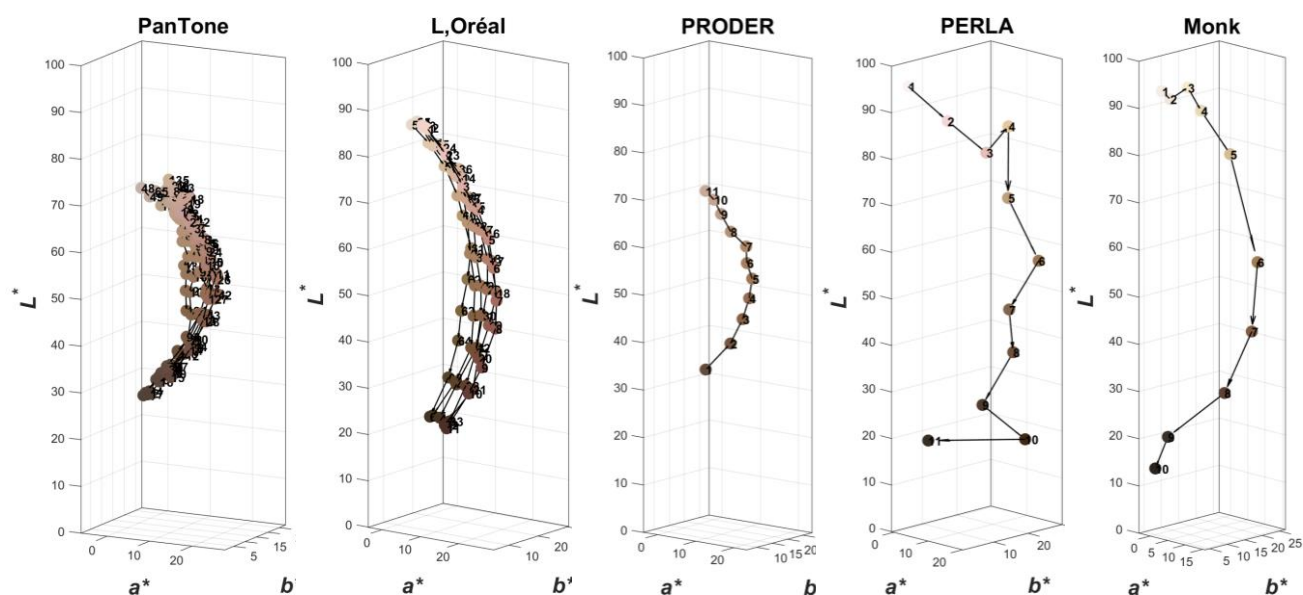


Figure 7-3 3D visualizations of the distribution of each skin scale in the CIELAB space.

After examining the range of skin tones across different scales, the analysis shifts to the step variations between individual tones within each scale, analyzing whether these steps are uniform or exhibit distinctive patterns. Both the PANTONE scale and the L'Oréal scale are divided into multiple hue groups, with the PANTONE scale containing 11 groups and the L'Oréal scale comprising 6 groups. The analysis begins by examining the distribution characteristics of hue angles within each group for these two scales.

Table 7-2 presents the mean and standard deviation of hue angles, as well as the mean perceptual hue difference, for each group in both the PANTONE and L'Oréal scales. The mean perceptual hue difference, commonly used to evaluate the performance of chromatic adaptation transforms [132], is

calculated using the following equations:

$$\overline{\Delta H} = \frac{\sum_{i=1}^n |\Delta H_i|}{n} \quad (7-1)$$

$$\Delta H_i = 2\sqrt{C_R C_{Ti}} \sin\left(\frac{h_R - h_{Ti}}{2}\right) \quad (7-2)$$

In these equations, C_R and C_{Ti} represent the chroma of the reference stimulus and the i -th test stimulus, respectively, while h_R and h_{Ti} indicate the hue angles of the reference stimulus and i -th test stimulus. In this study, the reference stimulus is defined as the mean value of the corresponding hue group, and n represents the total number of skin tones within that hue group. The data presented in Table 7-2 show that the mean perceptual hue difference for each group in the L'Oréal scale does not exceed 1.00, with the maximum standard deviation of hue angle being 3.72°, observed at an average hue angle of 45.68°. In the PANTONE scale, the mean perceptual hue difference for each group remains below 1.10, with the maximum hue angle SD of 4.46° occurring at an average hue angle of 47.85°. Based on the data in Table 7-2, both the L'Oréal and PANTONE scale exhibit relatively consistent hue within each group.

Table 7-2 Mean and standard deviation of hue angle, as well as mean perceptual hue difference for each hue group in the PANTONE and L'Oréal skin tone scales.

Hue group	L'Oréal skin tone color scale			PANTONE skin tone guide		
	Mean perceptual hue difference $\overline{\Delta H}$	Hue angle Mean (°)	Hue angle SD (°)	Mean perceptual hue difference $\overline{\Delta H}$	Hue angle Mean (°)	Hue angle SD (°)
1	0.95	36.25	3.64	0.29	37.02	1.22
2	1.00	45.68	3.72	1.10	45.07	4.26
3	0.82	55.18	2.83	0.96	47.85	4.46
4	0.61	63.80	2.62	0.60	51.57	2.90
5	0.55	69.14	2.09	0.46	57.91	2.52
6	0.75	75.34	2.51	0.47	59.84	2.45
7	N/A	N/A	N/A	0.39	58.80	1.70
8	N/A	N/A	N/A	0.64	62.92	2.24
9	N/A	N/A	N/A	0.47	65.78	1.74
10	N/A	N/A	N/A	0.46	68.48	1.77
11	N/A	N/A	N/A	0.21	72.29	0.86

Although the hue values within each group of the two scales are relatively consistent, the variation between adjacent hue groups is not uniform, as shown in Figure 7-4. Figures 7-4(a) and (b) show the mean hue angle differences between adjacent hue groups for the PANTONE and L'Oréal scales, respectively. Figures 7-4(c) and (d) illustrate the distribution of these scales in the CIE a^*-b^* plane, with skin tones from the same group marked in the same color. The PANTONE scale consists of 138 skin tones, divided into 11 hue groups numbered from 5R to 6Y, with the number of colors in each group varying. L'Oréal scale includes 66 skin tones, divided into 6 groups, each containing 11 colors, and the groups are labeled from A to F. From Figures 7-4(a) and (b), it can be observed that the differences between groups are not consistent, particularly for the PANTONE scale, where the change in hue angle between groups 1Y and 2Y is even negative.

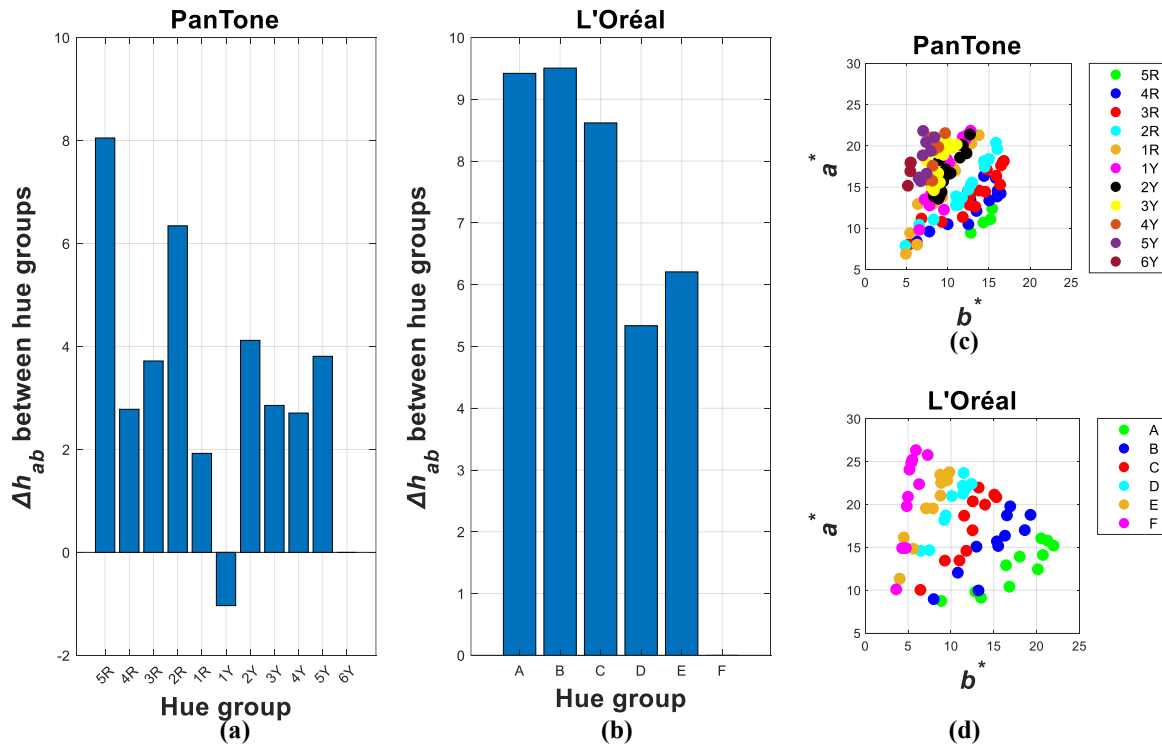


Figure 7-4 Mean hue angle differences between adjacent groups for the (a) PANTONE and (b) L'Oréal scales. Distribution of the (a) PANTONE and (b) L'Oréal scales in the a^*-b^* plane, with each skin tone within a group marked in the same color.

The color differences between adjacent skin tones within each group of the two scales were also calculated to assess the uniformity of color distribution within the groups. Figure 7-5 shows the total Euclidean color differences in the L^* and C_{ab}^* dimensions, calculated as $\sqrt{\Delta L^{*2} + \Delta C_{ab}^{*2}}$, and ΔE_{ab}^*

between adjacent skin tones within each group of the L'Oréal scale. Figure 7-6 provides the differences in the L^* and C_{ab}^* dimensions separately between adjacent skin tones within each group of the L'Oréal scale. It can be observed that the color variations within the L'Oréal scale groups are not entirely uniform, with both the $\sqrt{\Delta L^{*2} + \Delta C_{ab}^{*2}}$ or ΔE_{ab}^* ranging from approximately 6 to 9. In terms of the L^* dimension, the skin tones within each group generally exhibit a decreasing trend, while in the C_{ab}^* dimension, the change follows an initial increase followed by a decrease. Figures 7-7 and 7-8 show the $\sqrt{\Delta L^{*2} + \Delta C_{ab}^{*2}}$, ΔE_{ab}^* , and the differences in the L^* and C_{ab}^* dimensions between adjacent skin tones within each group of the PANTONE scale. The color differences $\sqrt{\Delta L^{*2} + \Delta C_{ab}^{*2}}$ and ΔE_{ab}^* within each group of the PANTONE scale are not uniformly distributed. In the L^* dimension, the skin tones generally exhibit a decreasing trend, although the last skin tone in the 1Y hue group shows an increase in L^* . In the C_{ab}^* dimension, the changes are more fluctuating, displaying a non-consistent pattern across the groups.

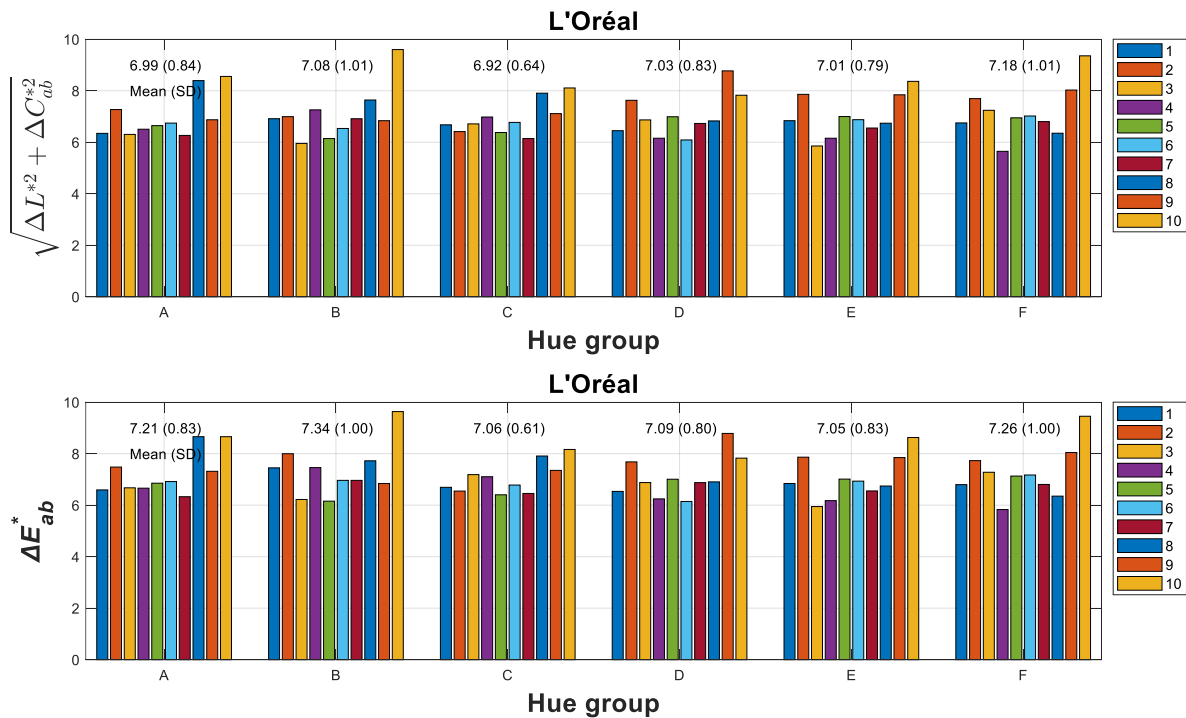


Figure 7-5 Color differences within the L'Oréal scale: total Euclidean color differences $\sqrt{\Delta L^{*2} + \Delta C_{ab}^{*2}}$ and ΔE_{ab}^* between adjacent skin tones in each hue group.

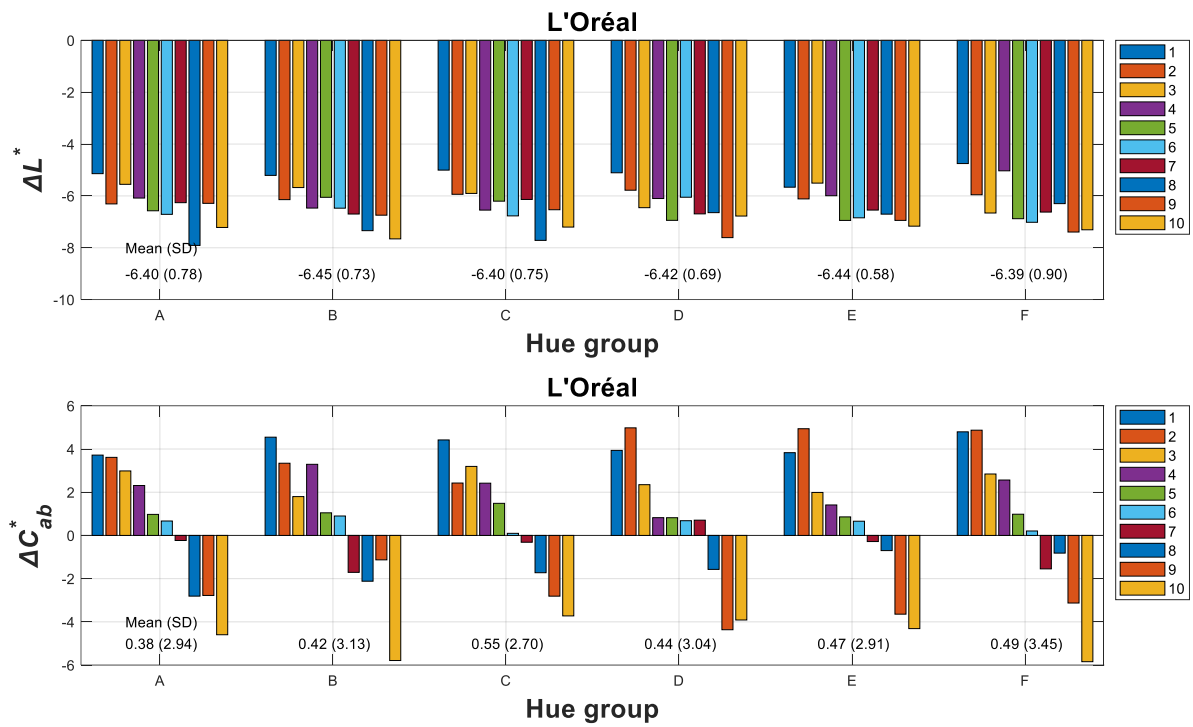


Figure 7-6 Differences in the L^* and C_{ab}^* dimension between adjacent skin tones in each hue group of the L'Oréal scale.

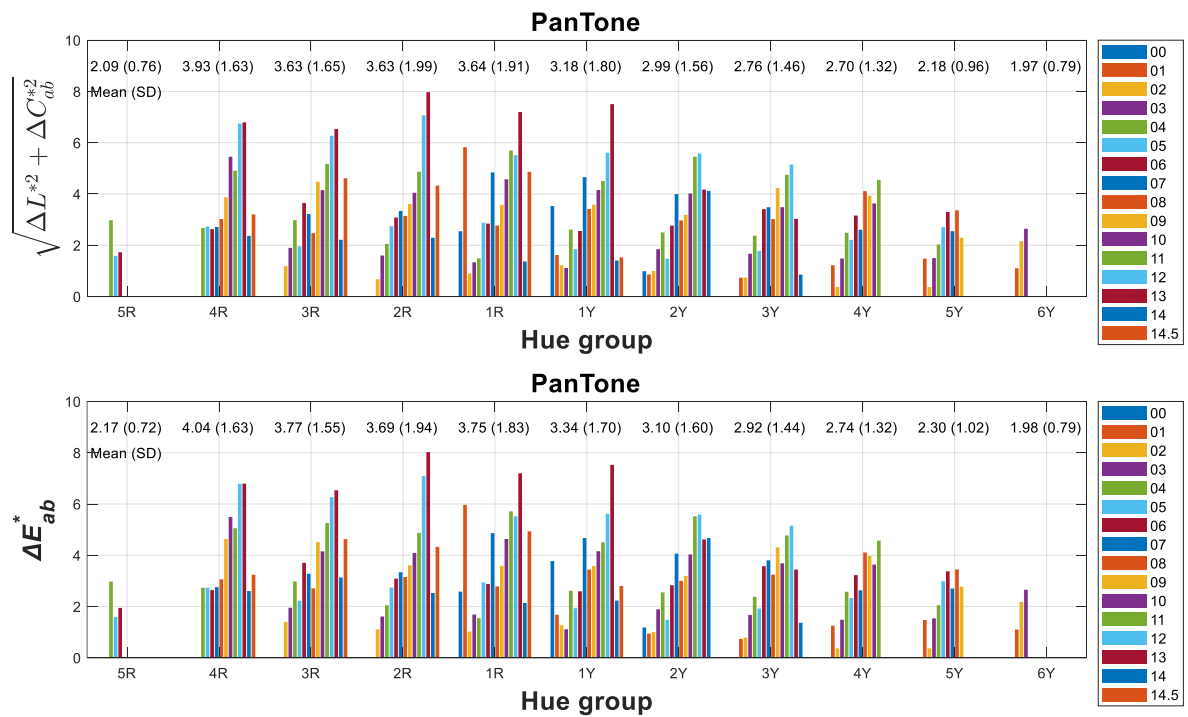


Figure 7-7 Color differences within the PANTONE scale: total Euclidean color differences $\sqrt{\Delta L^{*2} + \Delta C_{ab}^{*2}}$ and ΔE_{ab}^* between adjacent skin tones in each hue group.

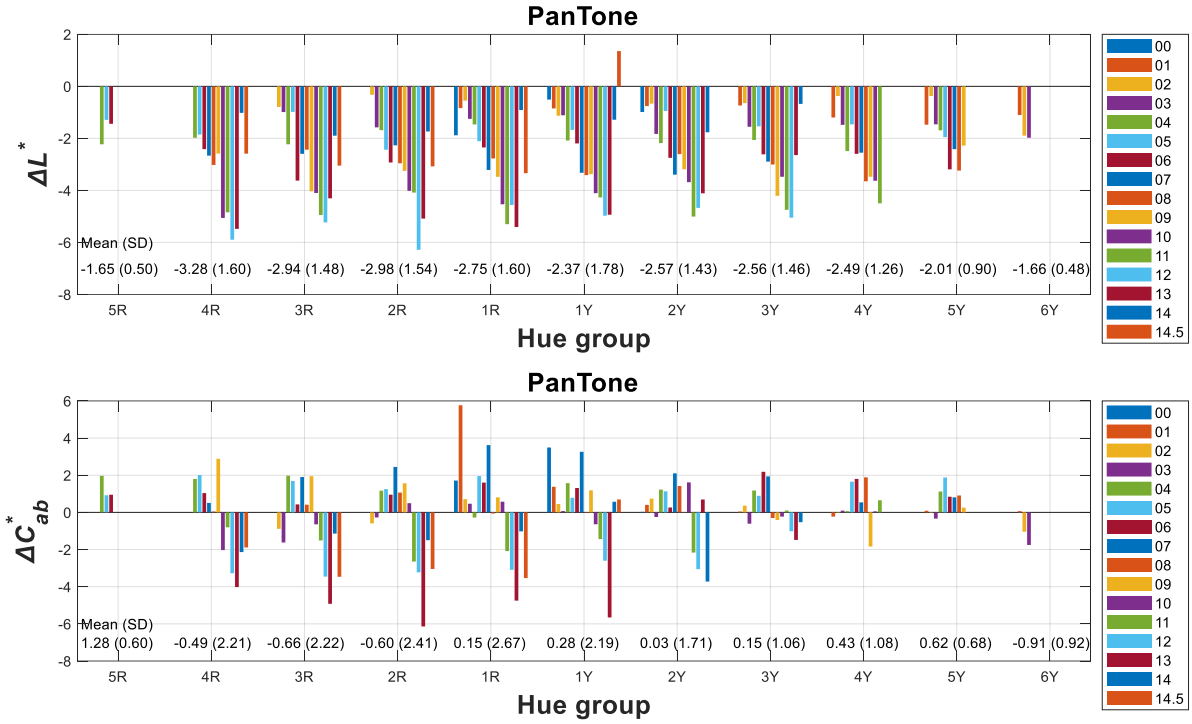


Figure 7-8 Differences in the L^* and C_{ab}^* dimension between adjacent skin tones in each hue group of the PANTONE scale.

Figures 7-9 to 7-11 illustrate the variations in ΔL^* , ΔC_{ab}^* , Δh_{ab} , and ΔE_{ab}^* between adjacent skin tones within the PRODER, PERLA, and Monk scales. The PRODER scale, which contains 11 skin tones, shows nearly uniform hue across the range, as shown in Figure 7-9(c). These tones exhibit an increasing trend in the L^* dimension and fluctuating changes in the C_{ab}^* dimension. However, the color differences ΔE_{ab}^* between adjacent skin tones in the PRODER scale are inconsistent.

The PERLA scale, also consisting of 11 skin tones, displays fluctuating variations in the L^* , C_{ab}^* , and h_{ab} dimensions. The ΔE_{ab}^* values between adjacent skin tones in the PERLA scale also show irregular changes, indicating an uneven distribution.

The Monk scale, which contains 10 skin tones, demonstrates fluctuating changes in the L^* and h_{ab} dimensions, with an initial increase followed by a decrease in the C_{ab}^* dimension. Similarly, the ΔE_{ab}^* values for adjacent skin tones in the Monk scale are uneven.

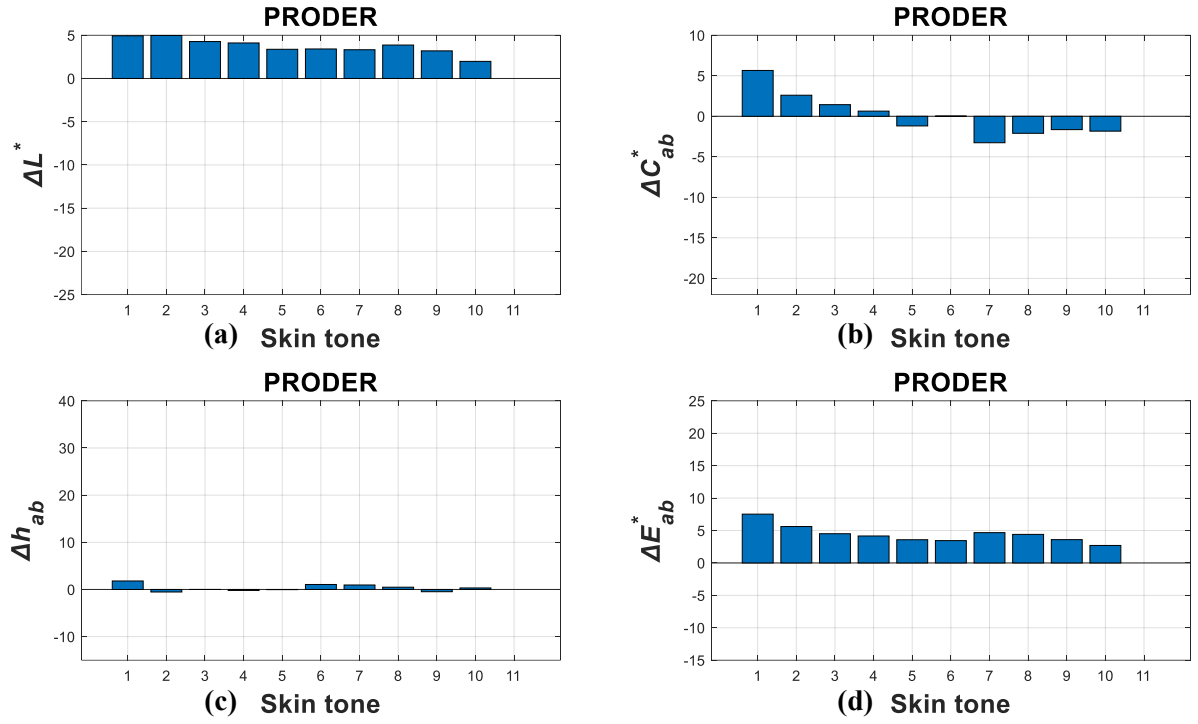


Figure 7-9 Variations in (a) ΔL^* , (b) ΔC_{ab}^* , (c) Δh_{ab} , and (d) ΔE_{ab}^* between skin tones within the PRODER scale.

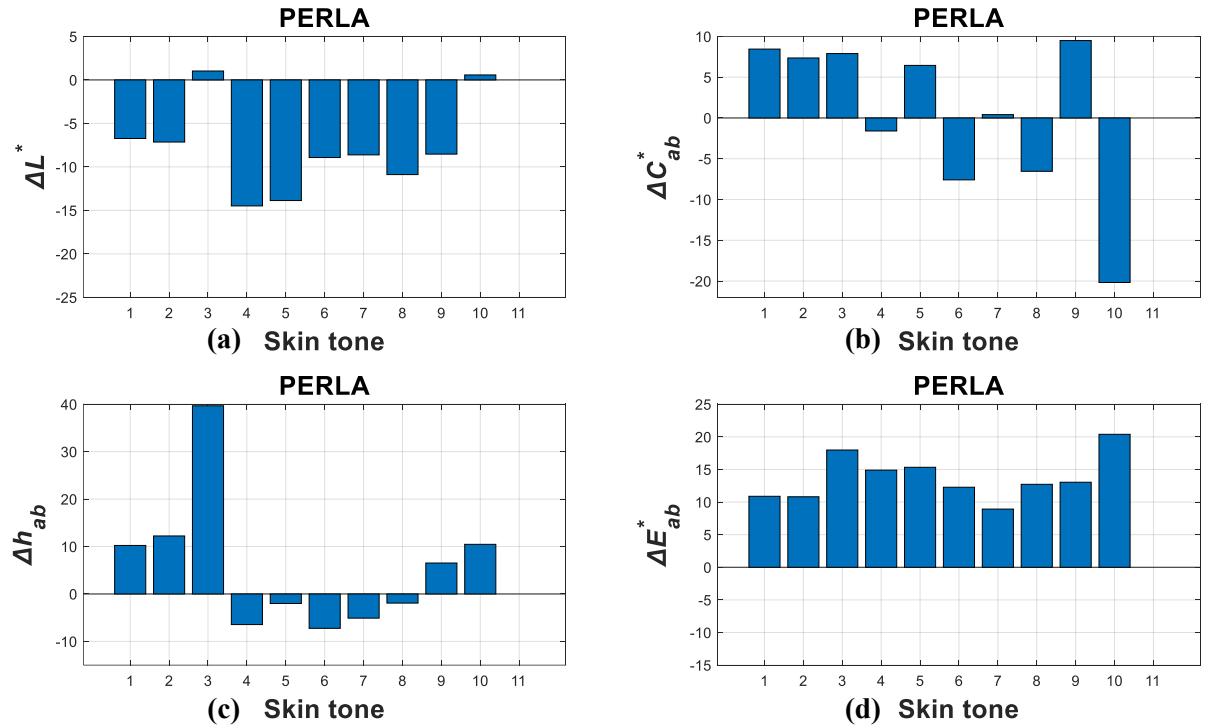


Figure 7-10 Variations in (a) ΔL^* , (b) ΔC_{ab}^* , (c) Δh_{ab} , and (d) ΔE_{ab}^* between skin tones within the PERLA scale.

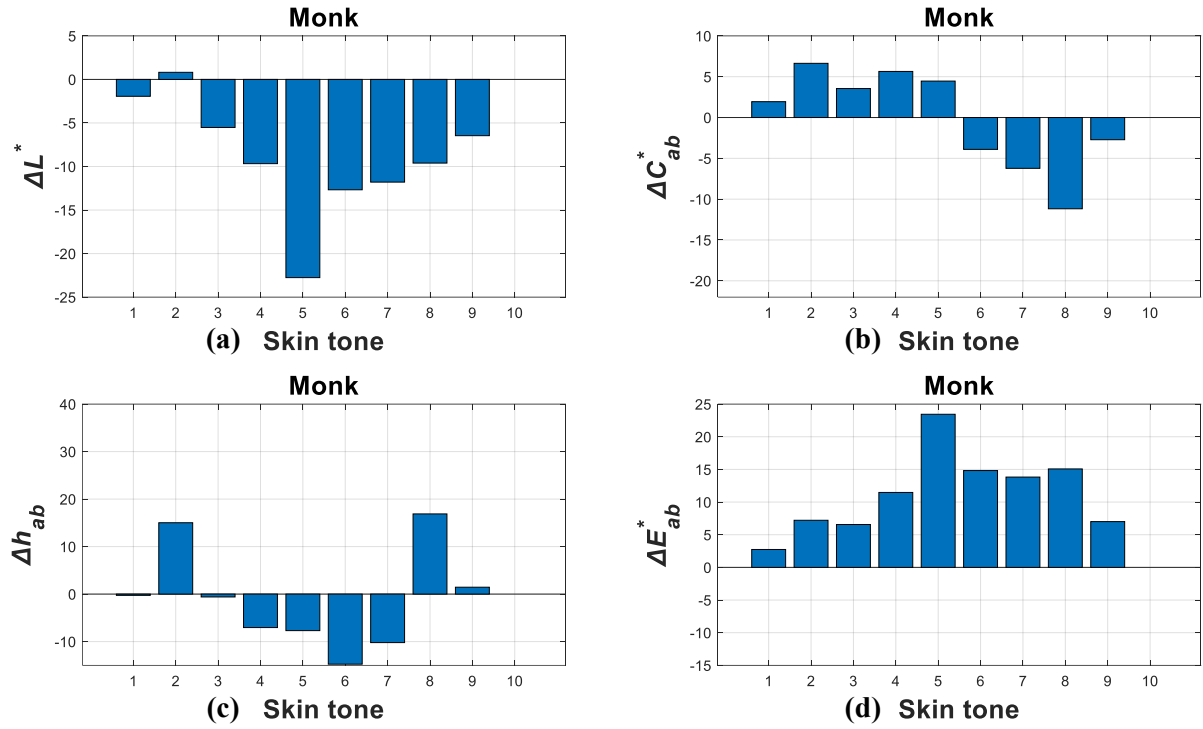


Figure 7-11 Variations in (a) ΔL^* , (b) ΔC^*_{ab} , (c) Δh_{ab} , and (d) ΔE^*_{ab} between skin tones within the Monk scale.

7.2.3 Biophysical properties of skin model

In the skin model, the appearance of skin color is influenced by both its structural organization and molecular composition. When constructing a skin model, it is essential to first define the assumed structure of the skin and then identify the variables that will be included in the model. To provide a foundation for understanding the modeling process, this section begins with an introduction to the structure and fundamental biophysical properties of human skin.

The human skin structure comprises three layers: the epidermis, dermis, and hypodermis [37]. The epidermis, as the outermost layer of the skin, varies in thickness from 12.7 to 200.1 μm [133]. It is divided into two sublayers: the stratum corneum and the living epidermis. The chromophore content in the stratum corneum is negligible and can be considered too low to affect skin color significantly [36]. In contrast, the living epidermis plays a critical role in determining the visible appearance of skin color, as it contains pheomelanin, responsible for the red or yellow tint observed in certain skin tones, and eumelanin, which contributes to the brown or black hues.

Beneath the epidermis lies the dermis, a significantly thicker layer with a depth ranging from

approximately 1 to 4 mm [106]. Due to its considerable thickness compared to the epidermis, the dermis is often modeled as a semi-infinite medium in most skin models. The dermis is further subdivided into the papillary dermis and the reticular dermis. It contains a rich network of blood vessels and a higher concentration of chromophores that influence skin color, such as oxyhemoglobin, deoxyhemoglobin, β -carotene, bilirubin, and water. Below the dermis lies the hypodermis, a layer primarily composed of adipose tissue.

The complexity of a skin model depends largely on its intended application. In fields such as medicine and dermatology, a comprehensive skin color model is essential. However, for applications requiring real-time rendering, such as 3D gaming, simplified skin models are often used to reduce computational load. Some models assume that each skin layer is a homogeneous medium or even treat the skin as a single semi-infinite layer [36, 104]. While these simplifications facilitate calculations, they often result in significant discrepancies between the model outputs and the appearance of real skin. Other models account for greater structural complexity, assuming four-layer structures (stratum corneum, epidermis, papillary dermis, and reticular dermis) [43], or even six-layer structures (stratum corneum, granular layer, spinous layer, basal layer, papillary dermis, and reticular dermis) [108]. However, the stratum corneum and hypodermis are frequently neglected in modeling due to their low absorption rates [36].

Considering these factors, this study adopts a two-layer skin structure, a widely used structure in previous skin model research [106, 107, 134]. The epidermis, a critical component influencing the skin's optical properties, is treated as a finite layer with a variable thickness ranging from 10 to 200 μm . The dermis is modeled as a semi-infinite layer, consistent with assumptions in many previous studies [36, 106]. The structure and chromophores used in our model are summarized in Table 7-3.

In this study, the spectral absorption properties of chromophores are considered in the skin model to characterize skin color accurately. Among the chromophores in human skin, melanin and hemoglobin are identified as the dominant contributors to light absorption and thus play a central role in determining the skin's color appearance [104].

Other chromophores, such as bilirubin and beta-carotene, also influence absorption and, consequently, the overall skin tone. For instance, substances such as bilirubin and beta-carotene contribute a

yellowish hue to the skin [51]. Thus, the bilirubin and beta-carotene were incorporated as additional chromophores to improve the performance of the skin model.

Table 7-3 Skin model structure and absorption coefficients of chromophores used in our skin model.

Skin structure	Thickness in model	Chromophore	Absorption coefficient (cm^{-1})
Epidermis	10 to 200 μm	pheomelanin	$2.9 \times 10^{15} \lambda^{-3.22}$ [108]
		eumelanin	$6.6 \times 10^{11} \lambda^{-3.22}$ [108]
		baseline	$7.84 \times 10^8 \lambda^{-3.255}$ [135]
Dermis	Semi-infinite	oxyhemoglobin	[136]
		deoxygenated hemoglobin	[136]
		baseline	$7.84 \times 10^8 \lambda^{-3.255}$ [135]

The absorption properties of the skin are described using the absorption coefficient μ_a . In the skin model, the dermis and epidermis are each characterized by their own μ_a values, which represent the combined contribution of all chromophores present within each layer [106]. The absorption coefficient μ_a for each layer, as described in [51], is calculated as the sum of the absorption contributions from all chromophores present in that layer. This is expressed mathematically as:

$$\mu_a(\lambda) = \sum_i f_{v_i} \mu_{a_i}(\lambda) \quad (7-3)$$

where λ is the wavelength of light in nanometers, μ_{a_i} is the absorption coefficient of the i -th chromophore, and f_{v_i} is the volume fraction of the i -th chromophore present in this layer. of i -th chromophore. The absorption coefficient μ_a can also be expressed using the following equation when the chromophore's concentration C_i (mol/L) and extinction coefficient ε_i ($L \cdot cm^{-1} \cdot mol^{-1}$) are known:

$$\mu_a(\lambda) = \ln(10) \sum_i C_i \varepsilon_i(\lambda) \quad (7-4)$$

The absorption coefficient of the epidermis is represented using the Equation (7-5):

$$\mu_{a_{epidermis}} = V_m (V_{eu} \mu_{a_{eu}} + (1 - V_{eu}) \mu_{a_{pheo}}) + (1 - V_m) (\mu_{a_{baseline}} + \mu_{a_{\beta-c}}) \quad (7-5)$$

where V_m is the volume fraction of melanin in the epidermis, V_{eu} is the fraction of eumelanin within

the total melanin content, $\mu_{a_{eu}}$ is the absorption coefficient of eumelanin, $\mu_{a_{pheo}}$ is the absorption coefficient of pheomelanin, $\mu_{a_{\beta-c}}$ is the absorption coefficients of beta-carotene, $\mu_{a_{baseline}}$ is the baseline absorption due to other components in the skin, such as keratin or water. For the dermis, the absorption coefficient is described as:

$$\mu_{a_{dermis}} = V_h \left(V_{hbO_2} \mu_{a_{hbO_2}} + (1 - V_{hbO_2}) \mu_{a_{hb}} + \mu_{a_{bil}} + \mu_{a_{\beta-c}} \right) + (1 - V_h) \mu_{a_{baseline}} \quad (7-6)$$

where V_h is the volume fraction of hemoglobin in the dermis, V_{hbO_2} is the fraction of oxyhemoglobin, $\mu_{a_{hbO_2}}$ is the absorption coefficient of oxyhemoglobin, $\mu_{a_{hb}}$ is the absorption coefficient of deoxygenated hemoglobin, $\mu_{a_{bil}}$ is the absorption coefficients of bilirubin.

The absorption coefficients of eumelanin, pheomelanin, oxyhemoglobin, deoxygenated hemoglobin, and baseline are known, as documented in Table 7-3. The absorption coefficients of eumelanin of bilirubin and beta-carotene are provided in [137, 138]. The absorption coefficients of oxyhemoglobin and deoxygenated hemoglobin, calculated using Equation (7-4), are based on wavelength-dependent tabulated data provided in [136]. The absorption coefficients for the chromophores used in the model are shown in Figure 7-12.

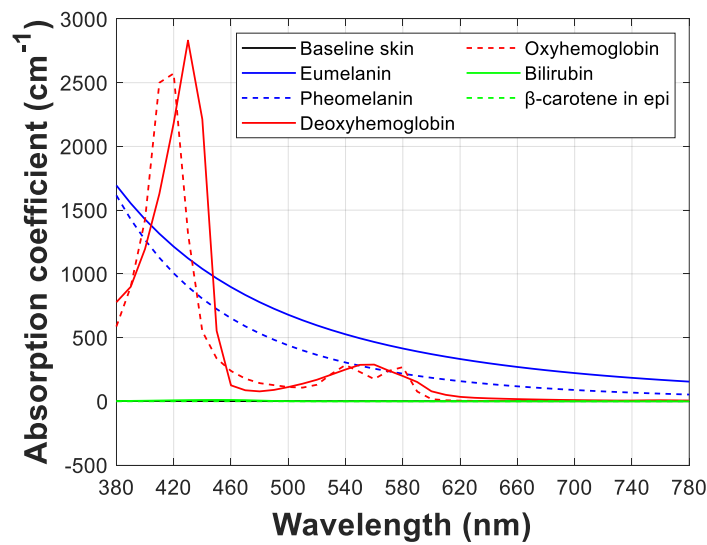


Figure 7-12 Absorption coefficients for the chromophores used in our skin model.

The only unknowns in the Equations (7-5) and (7-6) are V_m , V_{eu} , V_h , and V_{hbO_2} , which are the variables of this skin model, determining the contributions of the respective chromophores to the skin's overall absorption characteristics. The range for each four volume fraction variables is defined from 0 and 1. The scattering properties that influence skin appearance are characterized by the reduced scattering coefficient, which is expressed using the following formula [51]:

$$\mu'_s(\lambda) = a \left(f_{Ray} \left(\frac{\lambda}{500 \text{ (nm)}} \right)^{-4} + (1 - f_{Ray}) \left(\frac{\lambda}{500 \text{ (nm)}} \right)^{-b_{Mie}} \right) \quad (7-7)$$

where a is scaling factor used to generate a dimensionless value, f_{Ray} is the fraction of Rayleigh scattering, $(1 - f_{Ray})$ corresponds to the fraction of Mie scattering, and b_{Mie} is the scattering power of the Mie scattering component. The reference wavelength of 500 nm is chosen for normalization. Jacques [51] fitted the parameters across different datasets, and based on these, the mean values of $a = 48.0$, $f_{Ray} = 0.41$, and $b_{Mie} = 0.702$ were obtained. These mean values are applied in this study. The reduced scattering coefficients of the epidermis and dermis are assumed to be identical.

7.2.4 Simulation method of skin model

Accurately modeling the spectral reflectance of skin requires simulating the propagation of light within skin tissues, primarily accounting for absorption and scattering interactions. Two primary approaches exist for this simulation: deterministic and nondeterministic methods. In this study, both types of methods were explored. The Monte Carlo (MC) method, a widely adopted nondeterministic technique, is employed to simulate light transport in human skin. The MC method simulates photon movement in random step lengths, resulting in scattering and absorption events.

For this skin model, simulations were conducted from 380 to 780 nm in 10 nm intervals. Each simulation began with a light beam of 500 photons, each assigned an initial weight of 1. Each photon propagates in a random direction and moves in a randomly determined step length. After each step, the model evaluates whether the photon encounters a tissue boundary. If the photon reaches a boundary, it is either reflected or transmitted. If not, the photon is subjected to absorption and scattering events. This process is iterated until the photon's weight falls below a predefined threshold. Subsequently, the

roulette technique [115] is employed to determine whether the photon is terminated or continues propagating. The simulation continues until all photons have completed their paths, ultimately producing the skin's spectral reflectance within 380 to 780 nm. During the simulation, the refractive indices of both the epidermis and dermis are set to 1.4. Additionally, the anisotropy factor g for both layers is set to $0.62 + 0.29 \times 10^{-3}$, based on previous studies [36].

While the Monte Carlo (MC) method provides highly accurate results due to its minimal assumptions and photon-level simulations, it is computationally intensive, especially for large datasets. In contrast, the Kubelka-Munk (KM) method [139, 140] offers a simplified approach that is faster and less resource-intensive, though it sacrifices some of the detailed photon transport modeling inherent in the Monte Carlo method. As a deterministic method, the KM-based model approximates the light transport process by considering the medium as a homogeneous mixture of scattering and absorbing components. It means that the KM method does not simulate individual photons but rather uses effective coefficients to describe the interactions between light and the medium. The reflectance $R_{epidermis}$ and the transmittance $T_{epidermis}$ of the epidermis can be calculated using the KM method as follows:

$$R_{epidermis} = \frac{1}{a_{epidermis} + b_{epidermis} \coth(b_{epidermis} D \mu'_{s_{epidermis}})} \quad (7-8)$$

$$T_{epidermis} = \frac{b_{epidermis}}{a_{epidermis} \sinh(b_{epidermis} D \mu'_{s_{epidermis}})} + \frac{b_{epidermis}}{b_{epidermis} \cosh(b_{epidermis} D \mu'_{s_{epidermis}})} \quad (7-9)$$

$$a_{epidermis} = \frac{\mu_{a_{epidermis}} + \mu'_{s_{epidermis}}}{\mu'_{s_{epidermis}}} \quad (7-10)$$

$$b_{epidermis} = \sqrt{a_{epidermis}^2 - 1} \quad (7-11)$$

where $\mu_{a_{epidermis}}$ is the absorption coefficient of the epidermis, $\mu'_{s_{epidermis}}$ is the reduced scattering coefficient of the epidermis, D is the thickness of the epidermis layer. The dermis is assumed to be an infinitely thick layer in this model, which results in a different equation for the reflectance R_{dermis} ,

represented as:

$$R_{dermis} = a_{dermis} - b_{dermis} \quad (7-12)$$

$$a_{dermis} = \frac{\mu_{a_{dermis}} + \mu'_{s_{dermis}}}{\mu'_{s_{dermis}}} \quad (7-13)$$

$$b_{dermis} = \sqrt{a_{dermis}^2 - 1} \quad (7-14)$$

The total reflectance of the skin, considering both the epidermis and dermis, is given by:

$$R_{total} = R_{epidermis} + \frac{T_{epidermis}^2 R_{dermis}}{1 - R_{epidermis} R_{dermis}} \quad (7-15)$$

The Monte Carlo method, while providing high accuracy through detailed photon transport modeling, is computationally intensive. In contrast, the Kubelka-Munk method offers a more efficient alternative by simplifying the light transport assumptions, though it sacrifices some of the detailed modeling. Both methods have been employed in this skin model to simulate light propagation and estimate spectral reflectance.

7.3 Performance of our skin model

7.3.1 Result

The simulation results of our skin model are shown in Figures 7-13 and 7-14. Figure 7-13(a) presents the skin reflectance output from the MC method, with a fixed oxyhemoglobin volume fraction V_{hbO_2} of 50%, eumelanin volume fraction V_{eu} of 50%, epidermis thickness at $100 \mu m$, and melanin volume fraction V_h of 10%, while varying the hemoglobin volume fraction V_m from 10% to 50%. Figure 7-13(b) illustrates the corresponding skin reflectance when the hemoglobin volume fraction V_m is fixed at 10%, and the melanin volume fraction V_h is varied between 10% and 50%. In this case, all other variables (V_{hbO_2} , V_{eu} , epidermis thickness, and V_h) remain constant, with only V_h being varied. Figures 7-14(a) and (b) display the corresponding simulations using the KM method for the same variables as in Figures 7-13(a) and (b), respectively. These results provide a clear view of how the changes in the volume fractions of hemoglobin and melanin influence the skin reflectance across the spectral range.

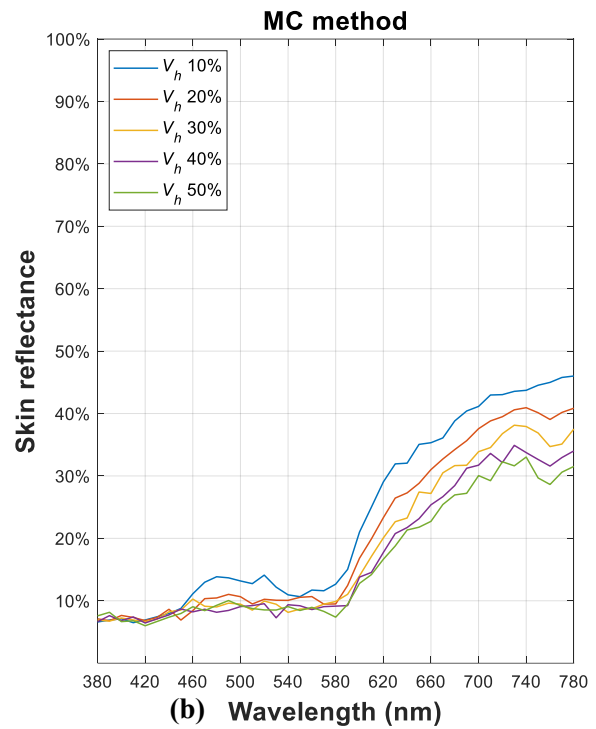
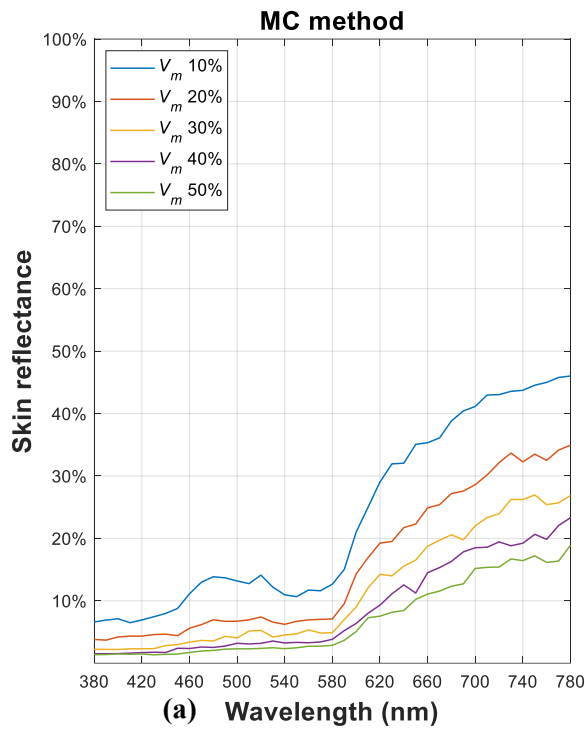


Figure 7-13 Simulated skin reflectance using the MC method: (a) varying hemoglobin volume fraction V_m (10%–50%), (b) varying melanin volume fraction V_h (10%–50%).

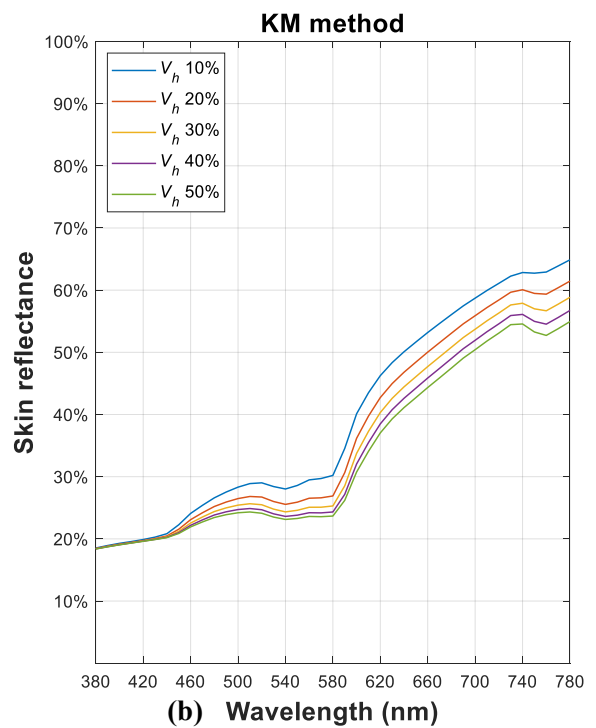
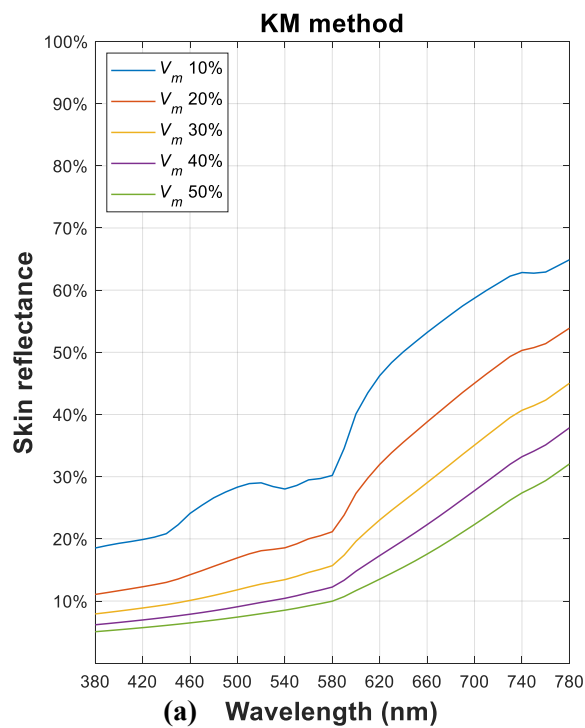


Figure 7-14 Simulated skin reflectance using the KM method: (a) varying hemoglobin volume fraction V_m (10%–50%), (b) varying melanin volume fraction V_h (10%–50%).

7.3.2 Effect of simulation method

The skin model's performance was evaluated using the previously introduced skin scales and the NIST dataset [141]. The NIST dataset contains 100 reference reflectance spectra of human skin, with no subject selection based on age, gender, or ethnicity. The NIST data were first converted to XYZ values using the CIE 1931 2° standard observer and D65 illuminant, and then to LAB values (with D65 as the reference), which were used to evaluate the skin model's performance. Beyond assessing its predictive accuracy, this section further evaluates the performance of the MC and KM methods by applying them to the previously analyzed skin scales.

Specifically, the RGB values of the skin tones from previously introduced scales were used to predict their corresponding reflectances via the skin model. The process began by converting the RGB values of the skin scales into XYZ values. The RGB values of most scales were confirmed to be in the sRGB color space, while the PERLA scale was identified as being in the Adobe RGB color space. This determination was made by examining the original images of the scales using the XnView software to retrieve their embedded color space information. The conversion from RGB values to XYZ values involved normalizing the RGB values by dividing by 255, applying a gamma correction, and then multiplying by the corresponding transformation matrix. Next, the XYZ values were transformed into the CIE LAB color space using the D65 illuminant as the reference white point. The resulting LAB values served as the input to the skin model.

To predict the optimal parameters of the skin model (V_m , V_{eu} , V_h , V_{hbO_2} , and epidermis thickness), an optimization was performed using MATLAB's `fmincon` function. This function minimized the color difference ΔE_{ab}^* between the actual LAB values of the skin scales and the LAB values derived from the skin model's reflectance predictions. During the optimization process, the volume fraction parameters (V_m , V_{eu} , V_h , V_{hbO_2}) were constrained to a range of 0 to 1, with initial values set to 0.5. The epidermis thickness was restricted to a range of 0.001 to 0.020, with an initial value of 0.010. The predicted reflectances were then converted into LAB values under the CIE 1931 2° standard observer and D65 illuminant.

The performance of the skin model was evaluated by calculating the color differences ΔE_{ab}^* between

the predicted and actual LAB values for each scale. Using the MC method, the ΔE_{ab}^* values were 1.04 for the PANTONE scale, 1.72 for the L'Oréal scale, 1.73 for the PRODER scale, 4.34 for the PERLA scale, 2.93 for the Monk scale, and 2.40 for the NIST data. In comparison, the ΔE_{ab}^* values obtained using the KM method were 0.11 for the PANTONE scale, 1.50 for the L'Oréal scale, 0.05 for the PRODER scale, 4.26 for the PERLA scale, 2.69 for the Monk scale, and 1.30 for the NIST data.

The results suggest that the KM method consistently achieves lower ΔE_{ab}^* values across all scales, indicating superior predictive performance. The MC method has unique advantages, particularly its ability to account for complex light-tissue interactions, which makes it irreplaceable in scenarios requiring detailed modeling of light transport. Nonetheless, due to its high computational cost, this study limited the number of photons to 500 per wavelength, a configuration that impacted the MC method's predictive accuracy. Furthermore, the KM method is computationally more efficient, providing a more practical and effective solution for the specific objectives of this study. Therefore, the following analyses in this study were conducted using the KM method.

7.3.3 Development of a skin model LUT

To enhance the characterization of skin color, a Look-up Table (LUT) was derived from the analysis of the skin scales and the skin model. The LUT was constructed by systematically varying the step sizes of the model parameters across their defined ranges. The selection of appropriate step sizes required analyzing the distribution of the predicted optimal parameters for skin scales.

Figures 7-15 to 7-19 show the histograms of the optimal parameters predicted by the skin model using the KM method for the five skin scales. The x-axis indicates the parameter value ranges, while the y-axis represents the count of parameters within each range for a specific scale. These histograms show the distribution patterns of the parameters across the scales.

From Figures 7-15 and 7-16, it can be observed that the V_{eu} and V_{hbO2} are approximately uniformly distributed between 0 and 1. Based on this observation, the step size for both V_{eu} and V_{hbO2} was set to 0.2, resulting in six evenly spaced data points for each parameter. In contrast, the histograms in Figures 7-17 and 7-18 show that the V_m and V_h are not uniformly distributed. Both parameters exhibit denser distributions in the range of 0 to 0.2, particularly for V_h . To match these distributions and ensure finer

granularity in regions where data are more densely concentrated, a segmented step size was applied, as detailed in Table 7-4 (Step Setting 1). Figure 7-19 shows that the distribution of epidermis thickness T is not densely concentrated within any specific range. Therefore, the step size was set to 0.001, with the range spanning from 0.001 to 0.021. The upper limit of 0.021 is slightly greater than the model's setting value of 0.02, ensuring that the spacing between data points remains consistent.

Table 7-4 Step settings of skin model parameters for generating the LUTs. The format “start:step:end” indicates the range and step size for each parameter. For example, “[0:0.05:0.2, 0.4:0.2:1]” indicates steps of 0.05 from 0 to 0.2 and steps of 0.2 from 0.4 to 1.

Parameters	Step setting 1	Step setting 2	Step setting 3	Step setting 4
V_m	[0:0.05:0.2, 0.4:0.2:1]	[0:0.02:0.2, 0.3:0.1:1]	[0:0.1:0.2, 0.6:0.4:1]	[0:0.05:0.2, 0.4:0.2:1]
V_h	[0:0.02:0.2, 0.4:0.2:1]	[0:0.01:0.2, 0.3:0.1:1]	[0:0.05:0.2, 0.6:0.4:1]	[0:0.01:0.1, 0.2:0.2:1]
V_{eu}	0:0.2:1	0:0.1:1	0:0.5:1	0:0.2:1
V_{hbO2}	0:0.2:1	0:0.1:1	0:0.5:1	0:0.2:1
T	0.001:0.002:0.021	0.001:0.001:0.021	0.001:0.005:0.021	[0.0001:0.002:0.010]

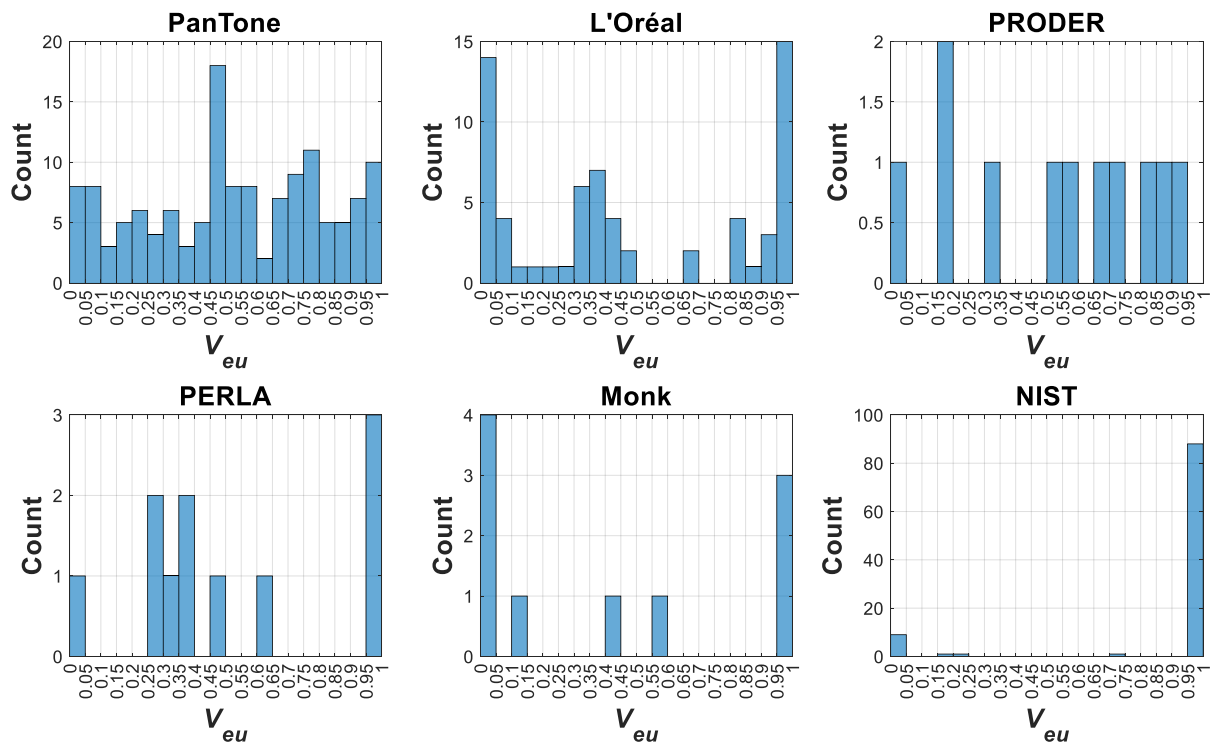


Figure 7-15 Histograms of the parameters V_{eu} predicted by the skin model using the KM method.

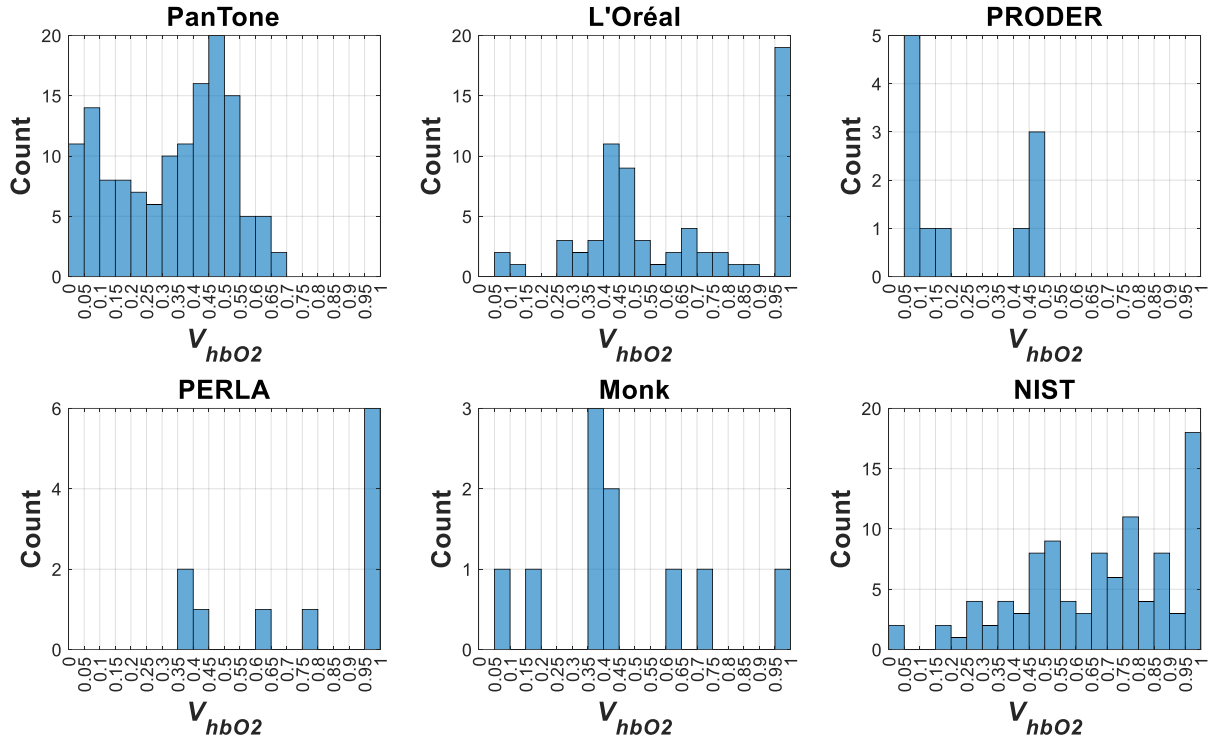


Figure 7-16 Histograms of the parameters V_{hbO2} predicted by the skin model using the KM method.

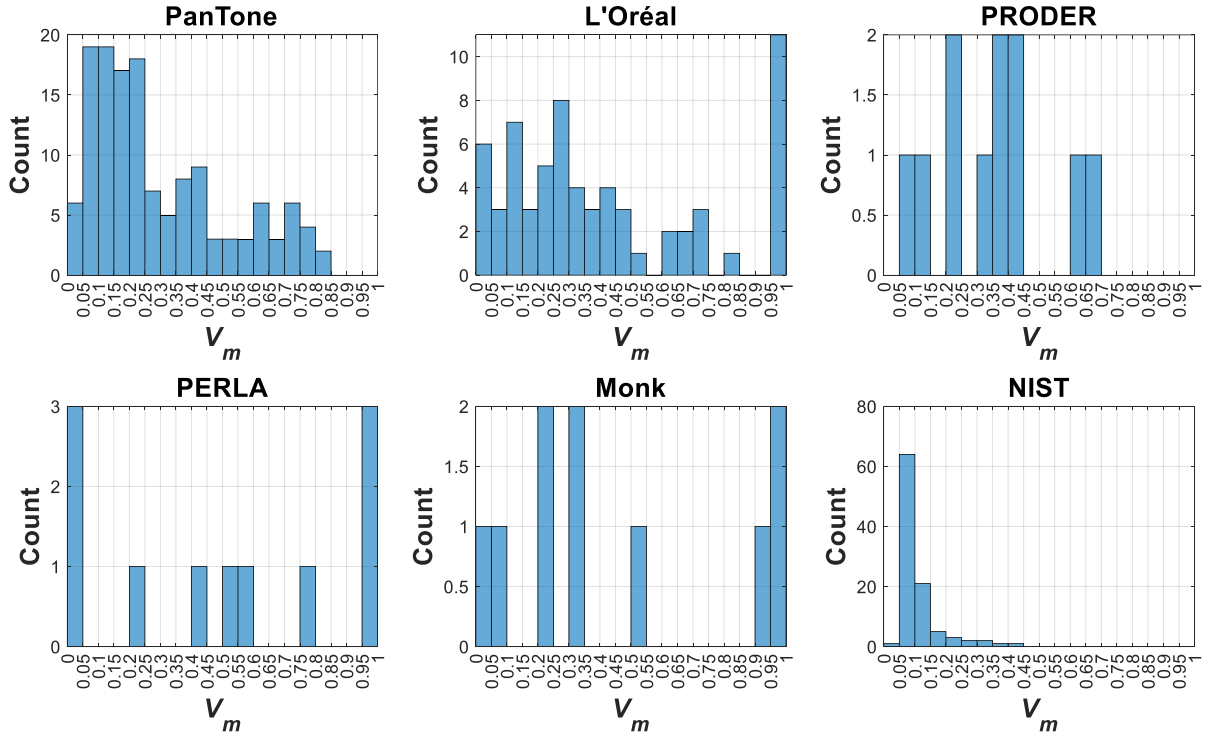


Figure 7-17 Histograms of the parameters V_m predicted by the skin model using the KM method.

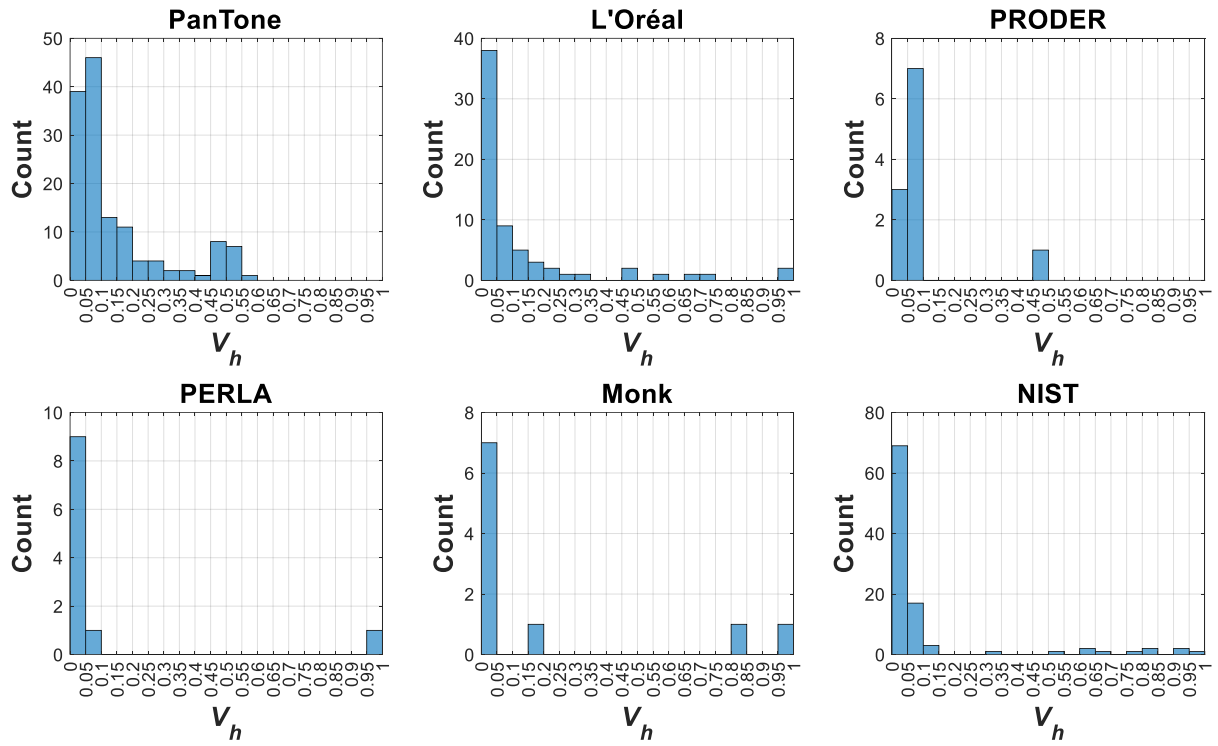


Figure 7-18 Histograms of the parameters V_h predicted by the skin model using the KM method.

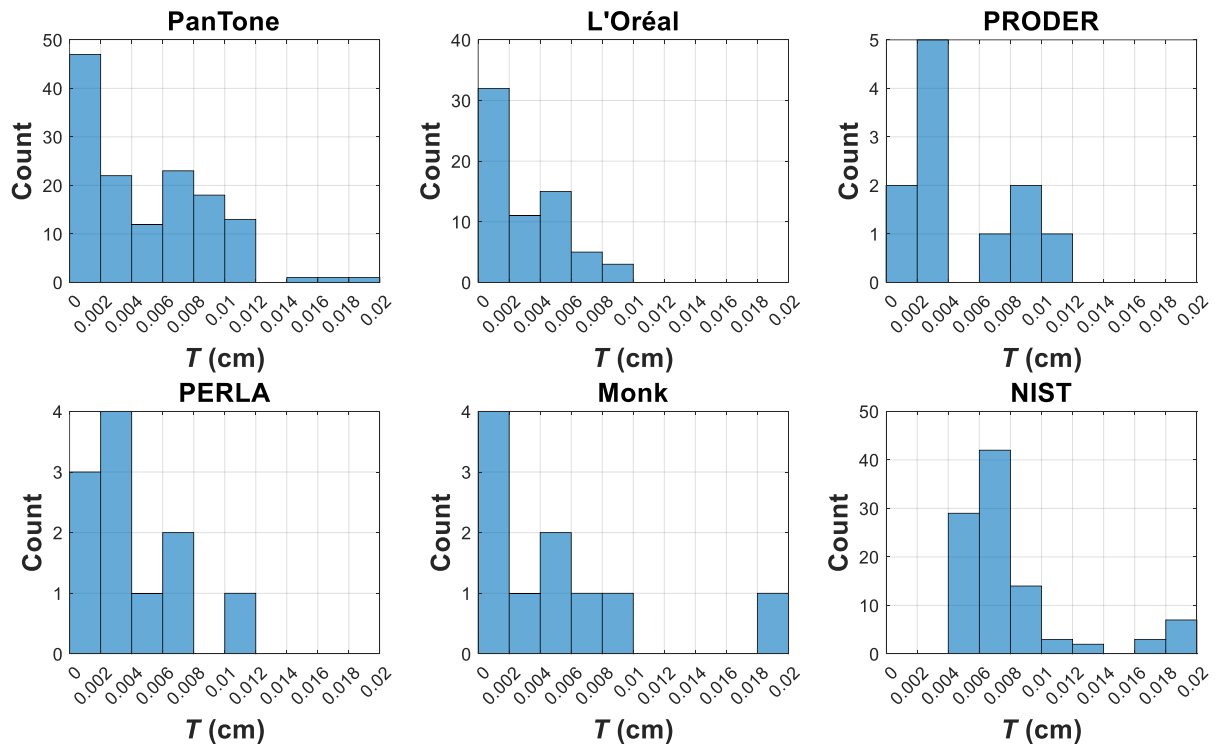


Figure 7-19 Histograms of the parameters T predicted by the skin model using the KM method.

Based on Step Setting 1 in Table 7-4, a LUT was generated, containing reflectance values paired with their corresponding LAB values. The LUT was then used to estimate the reflectance of the skin scales by identifying the LAB value within the LUT that minimizes the ΔE_{ab}^* between the predicted skin color and the skin color in the scale. The reflectance corresponding to this minimum ΔE_{ab}^* value was taken as the predicted value for the skin color. The results obtained using this method for each skin scale are presented in Table 7-5.

Table 7-5 Mean ΔE_{ab}^* predicted by different LUTs for the skin scales.

Skin scale	Step setting 1	Step setting 2	Step setting 3	Step setting 4
PanTone	0.73	0.30	1.86	0.76
L'Oréal	2.25	1.75	3.83	2.17
PRODER	0.66	0.22	2.13	0.58
PERLA	4.60	4.39	5.75	4.62
Monk	3.25	2.81	4.32	3.16
NIST	0.47	0.12	1.54	0.44

Additionally, more LUTs were generated using other step sizes, corresponding to step settings 2, 3, and 4, as outlined in Table 7-4. Step settings 2 and 3 have step sizes that are respectively smaller and larger than those of step setting 1. Step setting 4, compared to step setting 1, increases the density of the V_h range and decreases the density of the T range. The results predicted by these LUTs for skin scales are summarized in Table 7-5. It can be seen that step setting 2 yields the best performance, step setting 3 produces the worst, and step setting 4 performs better than step setting 1. However, step setting 2 generated 1,400,091 data points, nearly 26 times the number produced by step setting 1 (53460 data points), significantly increasing the computational cost and making it less practical. In contrast, step setting 4 only generated 31104 data points and outperformed step setting 1 in terms of predictive performance. Therefore, step setting 4 has been selected as the final configuration for our LUT.

To conclude, the development of the LUT with optimized step settings provides a more efficient approach for predicting skin reflectance across various skin scales. The selected final LUT configuration (step setting 4) balances computational feasibility and predictive performance, offering

a robust tool for further skin color modeling and analysis.

7.4 Experiment of skin color difference

7.4.1 Skin color centers

The LUT generated based on step setting 4 in Table 7-4 contains 31104 points, the distribution of which in the CIE LAB color space is illustrated in Figure 7-20. In Figure 7-20, the LUT points generated by the model (left) and those from all skin scales (right) are divided into $5 \times 5 \times 5$ cubes, with each cube's color representing the percentage distribution of points contained within it. A series of 2D plots was generated by segmenting the LUT along the a^* axis to further analysis. For instance, for a^* values between 15 and 20, a plot was produced with b^* on the horizontal axis and L^* on the vertical axis. In total, ten such plots were generated for a^* values ranging from -5 to 45. Figure 7-21 shows the plots for a^* values ranging from 5 to 10 and from 10 to 15. The remaining plots are presented in Figures 7-22 to 7-25.

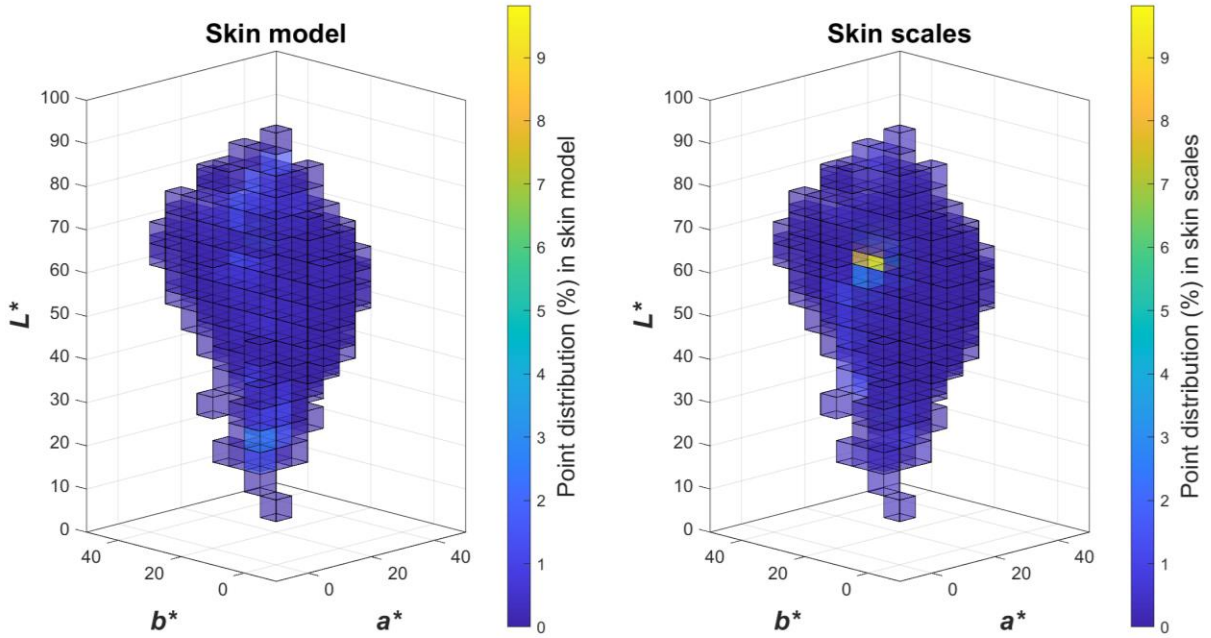


Figure 7-20 Distribution of our LUT points (left) and skin scale data (right) in the CIE LAB color space.

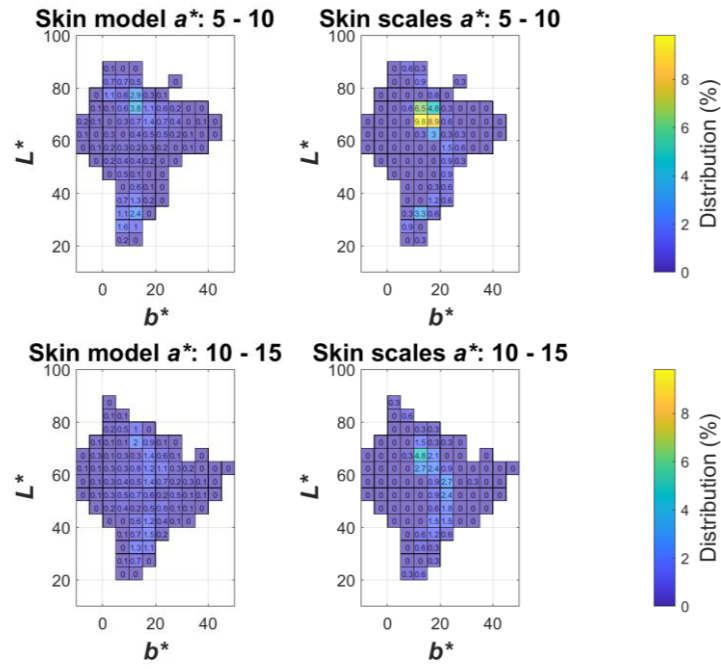


Figure 7-21 b^* - L^* distributions of LUT points for a^* values: from 5 to 10 (top) and from 10 to 15 (bottom).

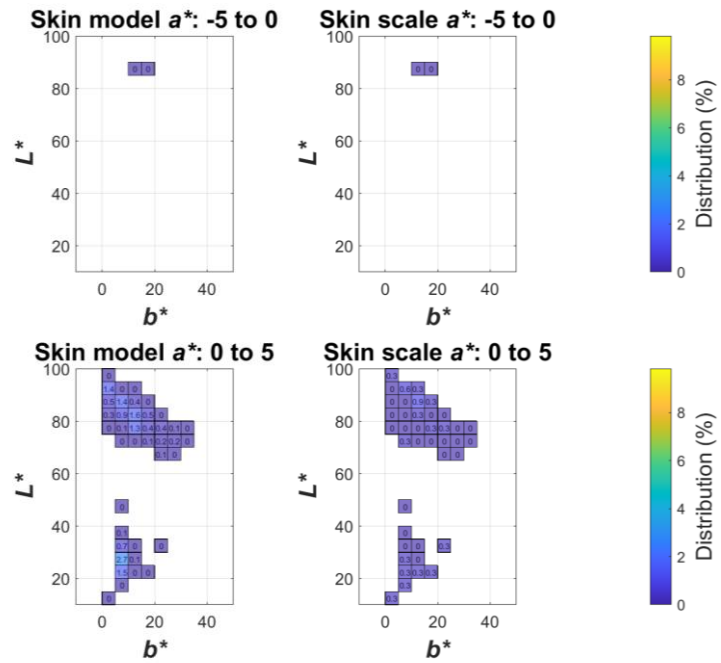


Figure 7-22 b^* - L^* distributions of LUT points for a^* values: from -5 to 0 (top) and from 0 to 5 (bottom).

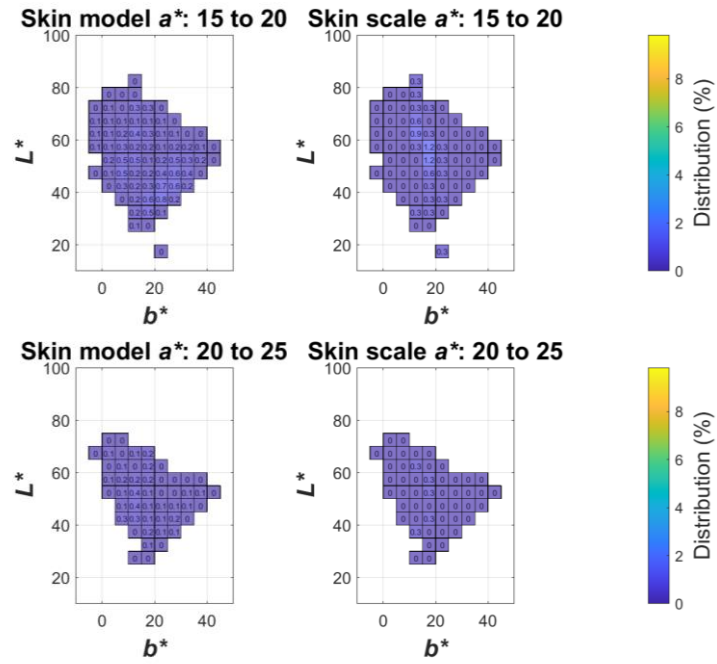


Figure 7-23 b^* - L^* distributions of LUT points for a^* values: from 15 to 20 (top) and from 20 to 25 (bottom).

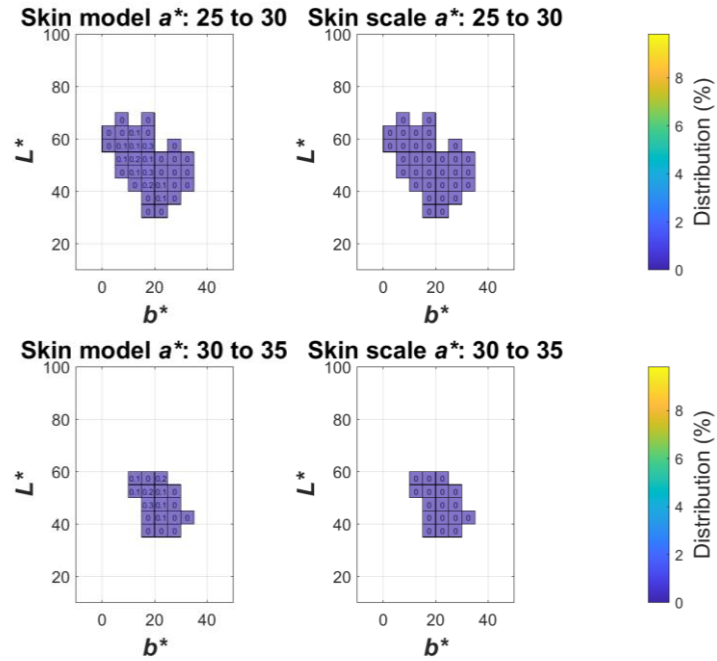


Figure 7-24 b^* - L^* distributions of LUT points for a^* values: from 25 to 30 (top) and from 30 to 35 (bottom).

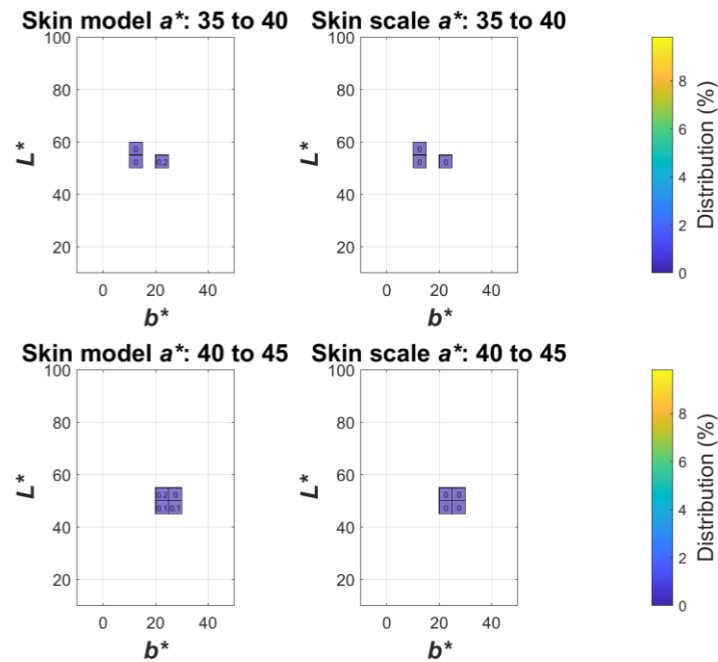


Figure 7-25 b^* - L^* distributions of LUT points for a^* values: from 35 to 40 (top) and from 40 to 45 (bottom).

The number displayed in each square of Figure 7-21 indicates the percentage distribution of points contained within that specific $5 \times 5 \times 5$ cube. For example, in the skin model, the cube defined by a^* values between 5 and 10, L^* values between 70 and 75, and b^* values between 10 and 15 contains 3.8% of the total points. By grouping eight adjacent cubes to form larger $10 \times 10 \times 10$ cubes, the percentage distribution within these larger cubes can be calculated to identify skin color centers. Combining data from the skin model and skin scales, three skin color centers were identified, as shown in Table 7-6. The range of each skin color center corresponds to a different ethnic group, which aligns with measurements from the previous study [131].

Table 7-6 L^* , a^* and b^* ranges for three skin color centers and the corresponding percentage distributions in the skin model and skin scales.

Corresponding ethnic groups	L^*	a^*	b^*	% distribution in the skin model	% distribution in skin scales
Caucasian	65-75	5-15	10-20	11.60%	38.70%
Asian	55-65	5-15	15-25	5.90%	11.60%
African	30-40	5-15	10-20	8.40%	7.70%

7.4.2 Method

A display (i.e., EIZO CS2740) with dimensions of 33.5 cm (width) $\times$ 60 cm (height) was used in the

experiment. A chin rest was mounted on the front of the display to maintain a similar viewing geometry for all observers. The display was chromatically characterized using the Piecewise Linear assuming Variation in Chromaticity (PLVC) display color characterization model [142]. Figure 7-26(a) shows the experimental setup, which was conducted in a dark environment. Two display white points (D65 and D95) were selected, with D65 serving as a widely used reference and D95 providing a clear chromatic contrast to examine their effects on the results. Figures 7-26(b), (c), and (d) show the GUI as seen by the observer during the experiment. The background of the GUI was set to gray. The reference stimulus was presented on the left, and the test stimulus was on the right. The size of the patch stimuli was designed to be $4 \times 4^\circ$ FOV. The skin color region of the face stimulus was designed to be approximately equal to the size of the patch stimulus. The distance between the reference stimulus and the test stimulus was set to 0.35 of the size of the patch stimulus. At the bottom of the GUI, there is a gray progress bar to indicate the progress of the experiment. At the top of the GUI, there is a white instruction that reminds observers to make a forced choice.

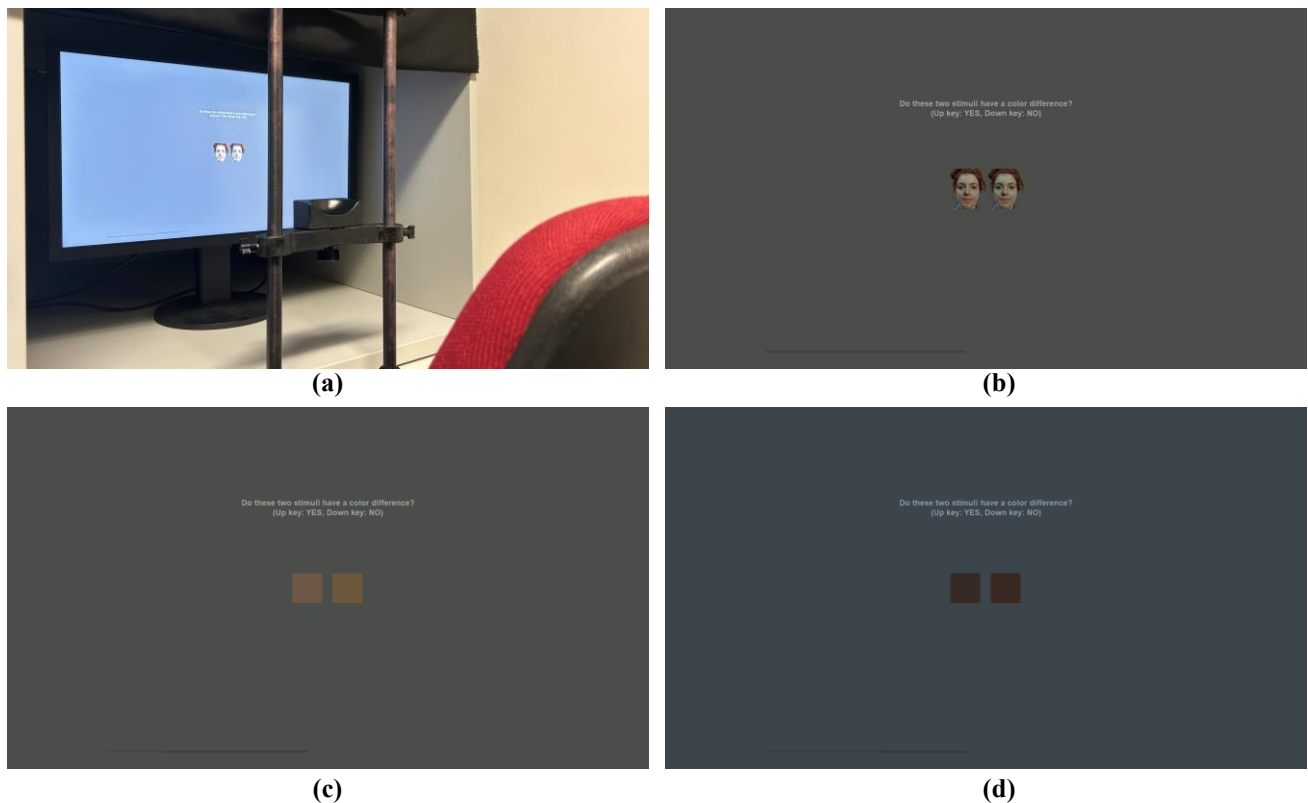


Figure 7-26 (a) Experiment setup and GUIs during the experiment of (b) face stimuli with Caucasian skin color under D65, (c) patch stimuli with Asian skin color under D65, and (d) patch stimuli with African skin color under D95.

Three facial images representing different ethnic groups (Caucasian, Asian, and African) were selected from the MST-E dataset [143] for the experiment. The images were cropped to retain only the facial region, and the original backgrounds were removed. Under the D65 white point, the CIELAB values of the reference stimuli were set to the three skin color centers identified in Section 7.4.1. Within each of the three LAB cubes defined in that section, a grid of $11 \times 11 \times 11$ points was generated at intervals of 1 unit in each dimension. The chromaticity coordinates of these points were computed in the CIE 1976 $u'v'$ chromaticity diagram, thereby defining the chromaticity range of each cube.

Within these ranges, the chromaticity coordinates of the test stimuli were uniformly sampled around the reference stimuli at an interval of 0.015. Under the D95 white point condition, both the reference and test stimuli were generated by applying the CAT02 chromatic adaptation transform to their corresponding stimuli under the D65 white point.

The generated chromaticity coordinates were treated as target values. Using the previously established PLVC model, the corresponding RGB values for these target chromaticities were computed. These RGB values were then applied to the display and measured to obtain the actual chromaticity coordinates. Due to device limitations, multiple measurements were conducted to determine the final RGB values used in the experiment. The resulting measured chromaticities were uniformly distributed within the intended target range.

Figures 7-27 and 7-28 show the calibrated test stimuli under D65 and D95, respectively. The first row shows 2D histograms (bin size = 0.0015) representing the uniformity of point distribution. Bins containing more than one point are drawn in yellow. The second row displays the measured chromaticities as red dots, with solid lines outlining the chromaticity boundaries for the target (red) and measured (blue) points.

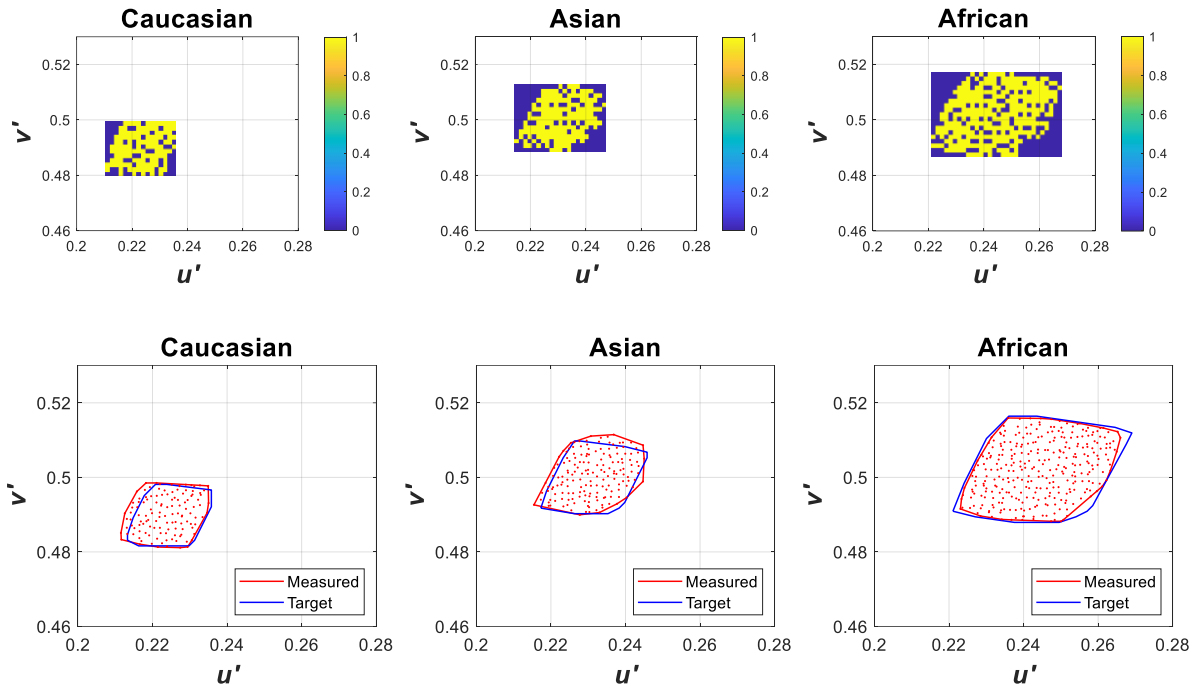


Figure 7-27 Distribution of calibrated test stimuli under D65. First row: 2D histograms of chromaticity point distribution (bin size = 0.0015). Second row: measured chromaticities (red dots), with boundaries of target (red) and measured (blue) chromaticity ranges.

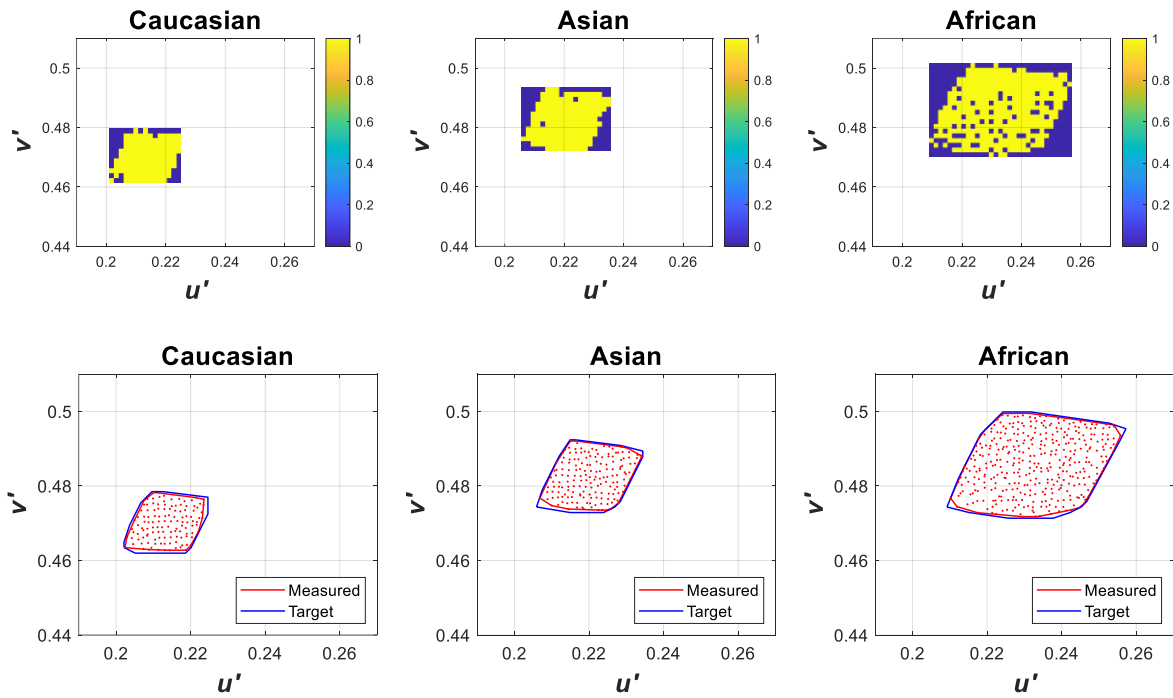


Figure 7-28 Distribution of calibrated test stimuli under D95, following the same color and symbol conventions as in Figure 7-27.

Under D65, there are 616 test stimuli in total, including 126, 170, and 320 points for Caucasian, Asian, and African skin colors, respectively. Under D95, there are 678 test stimuli in total, with 125, 173, and 380 points corresponding to the three skin colors. During the calibration process, the display's backlight signal was adjusted to ensure that the display white points under D65 and D95 conditions had approximately matched luminance levels. The target luminance values of the reference stimuli were calculated relative to the white point luminance under each condition. Therefore, slight differences in the white point luminance between D65 and D95 led to corresponding variations in the target Y values of the reference stimuli. Table 7-7 summarizes the target and measured chromaticities (u', v'), luminance (Y), and the maximum absolute luminance difference ($\max|\Delta Y|$) between test stimuli and reference stimuli for each condition.

Table 7-7 Summary of target and measured chromaticity coordinates, luminance, and the maximum absolute luminance difference between test and target reference stimuli for each condition.

White point	Race	Target (u', v')		Target Y	Measured (u', v')		Measured Y	$\max \Delta Y $
D65	Caucasian	0.2238	0.4891	32.38	0.2234	0.4896	32.76	2.26
	Asian	0.2308	0.4993	22.35	0.2307	0.4990	21.57	1.44
	African	0.2420	0.5014	6.75	0.2423	0.5023	5.69	1.29
D95	Caucasian	0.2126	0.4695	32.05	0.2123	0.4689	33.35	2.24
	Asian	0.2194	0.4819	22.04	0.2193	0.4816	21.89	1.99
	African	0.2302	0.4849	6.65	0.2314	0.4849	5.71	2.28

Ten observers (five males and five females) between 24 and 32 years of age (mean = 27.1, SD = 2.38) attended the experiment. All observers had normal color vision. The display was warmed up for 30 minutes before the experiment. Upon arrival, each observer completed an experimental information form and the Ishihara Color Vision Test. They then positioned their chin on the chin rest and completed a 2-minute dark adaptation.

Under each display white point, the experiment consisted of two sections. The first section presented face pairs, the second presented patch pairs. In these sections, observers judged whether a color difference existed between the test and reference stimuli. After dark adaptation, a stimulus pair was displayed, and observers made a forced-choice judgment by pressing the up or down arrow key (the up key indicated a color difference, while the down key indicated no difference). This procedure was repeated for all pairs, with the order randomized. Additionally, five pairs were randomly selected to

evaluate intra-observer variability.

Each observer completed 2588 judgments (616 pairs plus 678 pairs, across two sections) over two days, with one session for each white point lasting approximately 45 minutes per day. For each skin color under each white point, three stimuli were repeated, resulting in a total of 36 repeated pairs.

7.4.3 Results

The intra-observer variations were assessed through repeated judgments. There are 180 repeated judgments (18 pairs each observer) under each white point. Under D65, 173 out of 180 repeated judgments (about 96.1%) were consistent, while under D95, 177 out of 180 (about 98.3%) were consistent, indicating high intra-observer reliability.

The inter-observer variations were estimated by the difference between each observer's judgment and the average judgments, defined as the judgment agreed upon by more than half of the observers. Under D65, inter-observer agreement ranged from 90.5% to 97.2%, with an average of 94.9%. Under D95, agreement ranged from 86.6% to 98.2%, with an average of 95.5%, reflecting strong consistency in both conditions.

For each combination of white point, stimulus type, and skin color, a null conditional stimulus pair (i.e., the test stimuli were identical to the reference stimuli) was included to evaluate observer reliability. The proportion of participants who responded "no difference" to each of these pairs was calculated as the probability of observer reliability. With ten observers in total, a response rate of eight "no difference" judgments, for example, would correspond to a probability of 80%.

As shown in Figure 7-29, the null conditional probabilities for patch stimuli consistently follow the order of Caucasian > Asian > African under both D65 and D95. The probabilities for Caucasian and Asian skin colors reach or exceed 50%, suggesting that lower luminance may reduce perceptual reliability. Section 7.4.4 further discusses the influence of observer reliability.

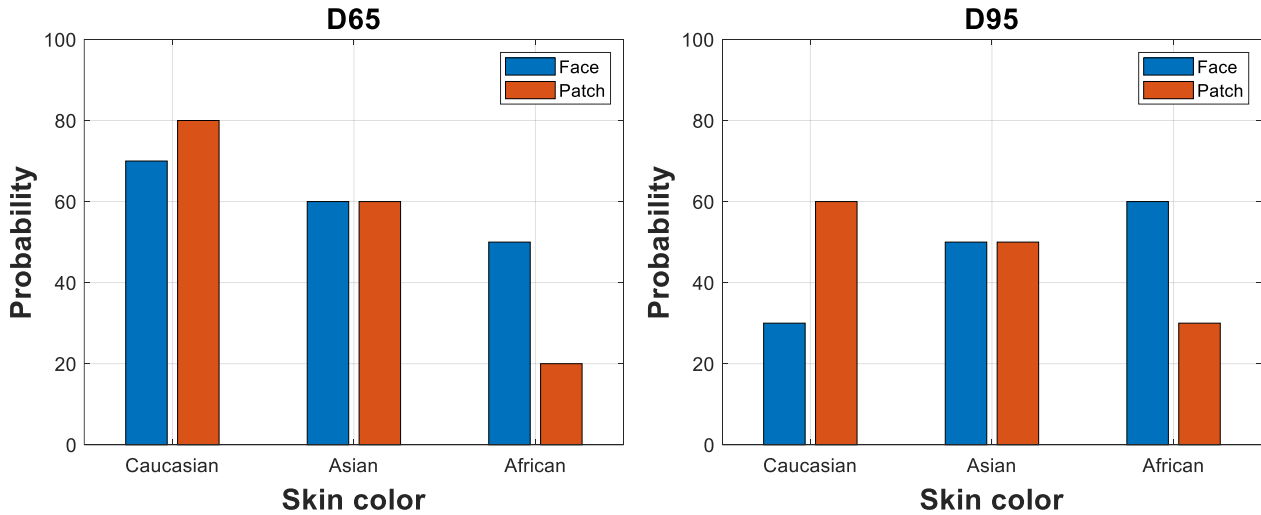


Figure 7-29 Null conditional probabilities under D65 and D95 white points.

Just Noticeable Color Difference (JNCD) represents the minimum color difference that can be perceived between two stimuli. The concept was derived from the work of MacAdam [144], who measured perceptual color discrimination thresholds and visualized them as ellipses, known as MacAdam ellipses. Estimating JNCD ellipses of skin colors is particularly valuable in image reproduction, color correction, and display calibration, where small deviations in skin colors may be perceptually critical. In this study, JNCD ellipses were estimated based on the chromaticities of test stimuli judged as having no color difference from the reference by a majority vote across observers.

Three types of ellipses were fitted: the one-standard-deviation ellipse [84], the three-standard-deviation ellipse, and the 95% confidence ellipse [145]. These ellipses share the same orientation and shape, differing only in size, with the 95% confidence ellipse corresponding to 2.45 standard deviations. Table 7-8 summarizes the fitted ellipse parameters for three skin colors and two stimulus types (face and patch) under D65 and D95 in the CIE 1976 $u'v'$ chromaticity diagram. The parameters include the semi-major axis a , semi-minor axis b , the geometric mean $\sqrt{ab}$, and the orientation angle θ .

The fitted ellipses for three skin colors and two stimulus types under D65 and D95 are shown in Figure 7-30. Solid lines represent face stimuli and dashed lines represent patch stimuli. The three skin colors, Caucasian, Asian, and African, are indicated by red, green, and blue, respectively. White points are marked by a black filled circle, and the reference stimuli for each skin color are denoted by black diamonds. “1-SD” and “3-SD” denote the one- and three-standard-deviation ellipses, respectively.

Table 7-8 Parameters of fitted ellipses for three skin colors and two stimulus types under D65 and D95 in the CIE 1976 $u'v'$ chromaticity diagram. Reported parameters include the semi-major axis a , semi-minor axis b , geometric mean $\sqrt{ab}$, and the orientation angle θ . “1-SD” and “3-SD” denote the one- and three-standard-deviation ellipses, respectively.

White point	Ellipse	Skin color	Face				Patch			
			a	b	θ (°)	$\sqrt{ab}$	a	b	θ (°)	$\sqrt{ab}$
D65	1-SD	Caucasian	0.0020	0.0010	51.78	0.0014	0.0024	0.0005	46.18	0.0010
		Asian	0.0028	0.0011	37.85	0.0018	0.0032	0.0011	44.32	0.0018
		African	0.0045	0.0010	63.18	0.0021	0.0026	0.0016	76.02	0.0020
	3-SD	Caucasian	0.0060	0.0030	51.78	0.0042	0.0072	0.0014	46.18	0.0031
		Asian	0.0084	0.0034	37.85	0.0053	0.0096	0.0032	44.32	0.0055
		African	0.0135	0.0029	63.18	0.0062	0.0079	0.0047	76.02	0.0061
	95% confidence	Caucasian	0.0049	0.0024	51.78	0.0034	0.0059	0.0011	46.18	0.0026
		Asian	0.0069	0.0028	37.85	0.0044	0.0079	0.0026	44.32	0.0045
		African	0.0110	0.0023	63.18	0.0051	0.0065	0.0038	76.02	0.0050
D95	1-SD	Caucasian	0.0024	0.0006	86.16	0.0012	0.0016	0.0005	90.04	0.0009
		Asian	0.0023	0.0009	72.50	0.0014	0.0025	0.0014	27.49	0.0019
		African	0.0058	0.0012	44.78	0.0026	0.0047	0.0021	19.82	0.0031
	3-SD	Caucasian	0.0072	0.0018	86.16	0.0036	0.0048	0.0014	90.04	0.0026
		Asian	0.0069	0.0026	72.50	0.0042	0.0075	0.0042	27.49	0.0056
		African	0.0174	0.0035	44.78	0.0079	0.0142	0.0063	19.82	0.0094
	95% confidence	Caucasian	0.0059	0.0015	86.16	0.0030	0.0039	0.0011	90.04	0.0021
		Asian	0.0056	0.0021	72.50	0.0034	0.0061	0.0034	27.49	0.0046
		African	0.0142	0.0029	44.78	0.0064	0.0115	0.0051	19.82	0.0077

Regardless of the adapting white point (D65 or D95) or stimulus type (face or patch), the African skin color consistently exhibits the largest $\sqrt{ab}$. In contrast, the Caucasian skin color yields the smallest. This pattern suggests higher perceptual sensitivity to color differences in lighter skin tones.

The orientation of JNCD ellipses varies among skin colors. Under D65, orientations are relatively similar, ranging from 37.8° to 63.2° for face stimuli and 44.3° to 76.0° for patch stimuli. Under D95, orientations show greater variability, ranging from 44.8° to 86.2° for face stimuli and from 19.8° to 90.0° for patch stimuli, indicating less stable or incomplete chromatic adaptation. Stimulus type also affects ellipse orientation, especially under D95, with pronounced differences for Asian and African skin colors. The absolute orientation differences between face and patch stimuli under D65 are 5.6°, 6.5°, and 12.8° for Caucasian, Asian, and African skins, respectively. These differences under D95 are 3.9°, 45.0°, and 25.0°.

JNCD ellipses were also fitted in the CIELAB color space, as shown in Figure 7-31, with corresponding parameters listed in Table 7-9. Since the GUI included a white instruction element, observers were visually aware of the display white point throughout the experiment. This makes the CIELAB space particularly relevant for analysis in this study, as it aligns with the observers' visual experience during the experiment.

Table 7-9 Parameters of fitted ellipses for three skin colors and two stimulus types under D65 and D95 in the CIELAB a^*-b^* plane.

White point	Ellipse	Race	Face				Patch			
			a	b	θ (°)	$\sqrt{ab}$	a	b	θ (°)	$\sqrt{ab}$
D65	1-SD	Caucasian	1.23	0.65	82.88	0.89	1.49	0.32	69.14	0.69
		Asian	1.45	0.70	68.38	1.01	1.86	0.64	70.65	1.09
		African	1.79	0.38	90.35	0.82	1.13	0.48	104.56	0.73
	3-SD	Caucasian	3.70	1.94	82.88	2.68	4.47	0.96	69.14	2.07
		Asian	4.35	2.09	68.38	3.02	5.57	1.92	70.65	3.27
		African	5.36	1.13	90.35	2.46	3.38	1.43	104.56	2.20
	95% confidence	Caucasian	3.02	1.59	82.88	2.19	3.65	0.78	69.14	1.69
		Asian	3.55	1.71	68.38	2.46	4.54	1.57	70.65	2.67
		African	4.38	0.92	90.35	2.01	2.76	1.17	104.56	1.79
D95	1-SD	Caucasian	1.39	0.34	115.21	0.69	0.97	0.32	115.41	0.56
		Asian	1.22	0.48	97.71	0.77	1.20	0.89	51.88	1.04
		African	1.35	0.45	74.48	0.78	1.10	0.89	33.93	0.99
	3-SD	Caucasian	4.17	1.03	115.21	2.07	2.92	0.96	115.41	1.68
		Asian	3.66	1.44	97.71	2.30	3.60	2.68	51.88	3.11
		African	4.05	1.36	74.48	2.35	3.30	2.68	33.93	2.97
	95% confidence	Caucasian	3.41	0.84	115.21	1.69	2.38	0.79	115.41	1.37
		Asian	2.99	1.17	97.71	1.87	2.94	2.19	51.88	2.54
		African	3.30	1.11	74.48	1.92	2.70	2.18	33.93	2.43

In the CIELAB color space, ellipse sizes for Asian skin consistently exceed those for Caucasian skin across all white points and stimuli. Moreover, for patch stimuli, sizes follow Asian > African > Caucasian under both D65 and D95, suggesting that the texture may lead to less consistent color perception. The orientation of the ellipses shows similar trends to those found in the $u'v'$ chromaticity diagram. Orientation values of the three skin colors are more similar under D65, but show greater differences under D95. The influence of stimulus type on ellipse orientation is also more pronounced under D95 in the CIELAB space, particularly for Asian and African skin colors.

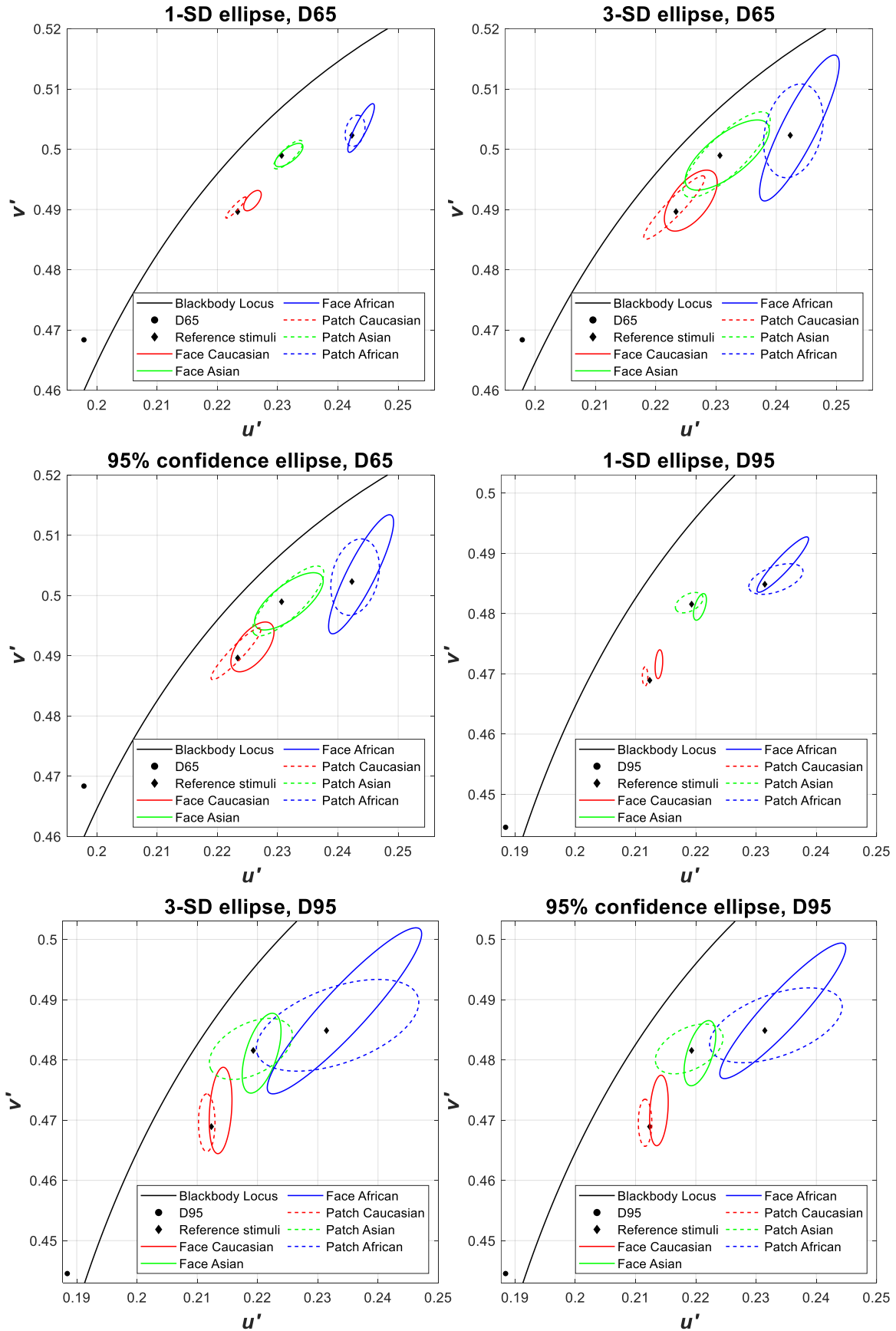


Figure 7-30 Fitted ellipses in the CIE 1976 $u'v'$ chromaticity diagram.

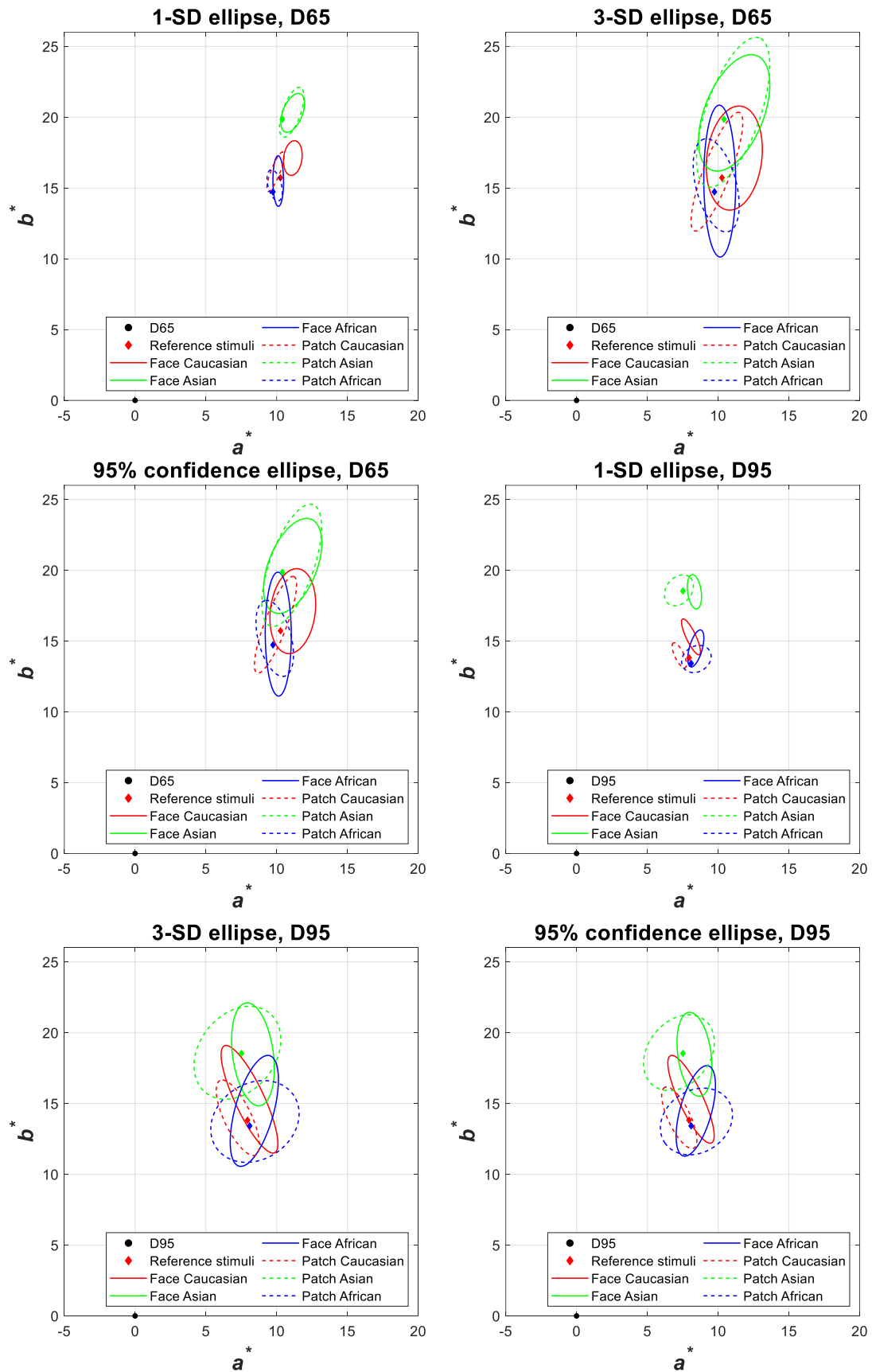


Figure 7-31 Fitted ellipses in the CIELAB a^* - b^* plane. The reference stimuli for each skin color are denoted by diamonds in the corresponding color.

7.4.4 Discussion

The null conditional probability analysis revealed that, for patch stimuli, the African skin color condition cannot reach a 50% agreement rate. In addition, the fitted one-standard-deviation ellipses showed that some conditions tended to deviate noticeably from the corresponding reference stimuli. These findings suggest that certain observers may have exhibited unreliable judgments.

To further investigate observer reliability, the scatters of test stimuli judged as “no difference” by each observer were plotted. For each combination of white point, stimulus type, and skin color, the chromaticity coordinates of these stimuli were plotted in the CIE 1976 $u'v'$ chromaticity diagram. The corresponding reference stimulus was shifted to the origin (0, 0) for normalization. Figures 7-32 and 7-33 show the results for patch stimuli under D65 and D95, respectively. Results for face stimuli are presented in Figures 7-34 and 7-35. Patch stimuli provide results that are not influenced by texture.

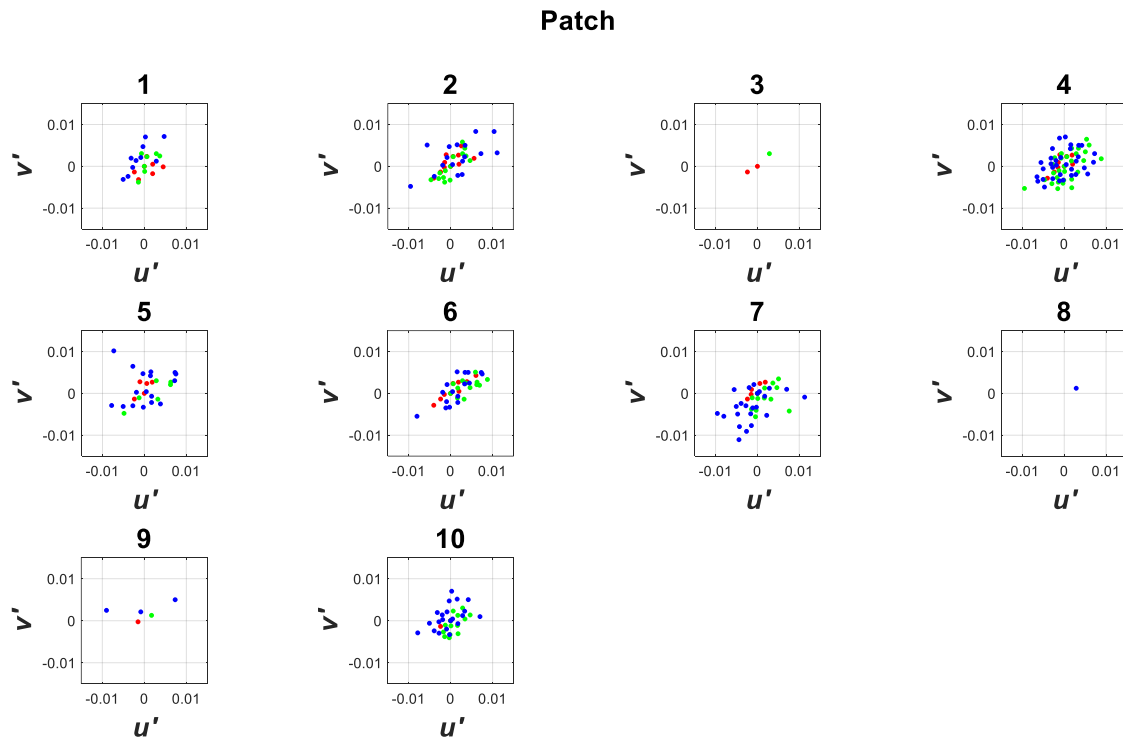


Figure 7-32 Test stimuli judged as “no difference” for patch stimuli under D65 in the CIE 1976 $u'v'$ chromaticity diagram. For each skin color (Caucasian: red, Asian: green, African: blue), the corresponding reference stimulus was shifted to the origin. Subplot titles indicate observer indices (1–10).

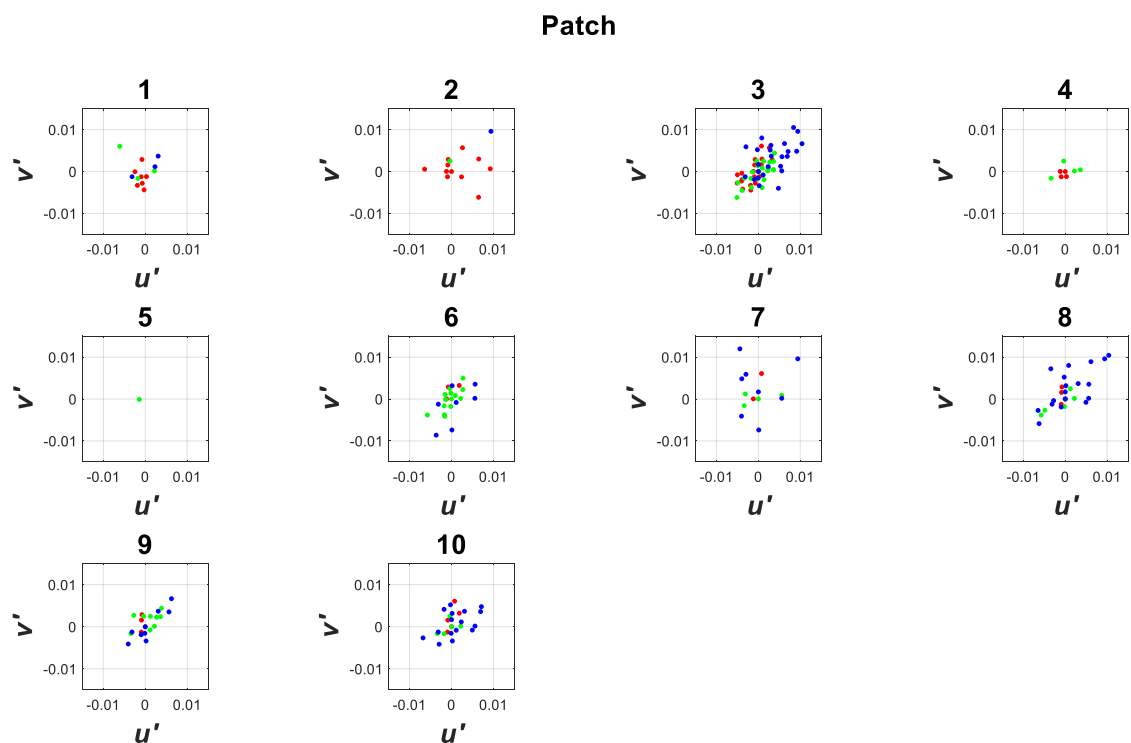


Figure 7-33 Test stimuli judged as “no difference” for patch stimuli under D95 in the CIE 1976 $u'v'$ chromaticity diagram, following the same symbol conventions as in Figure 7-32.

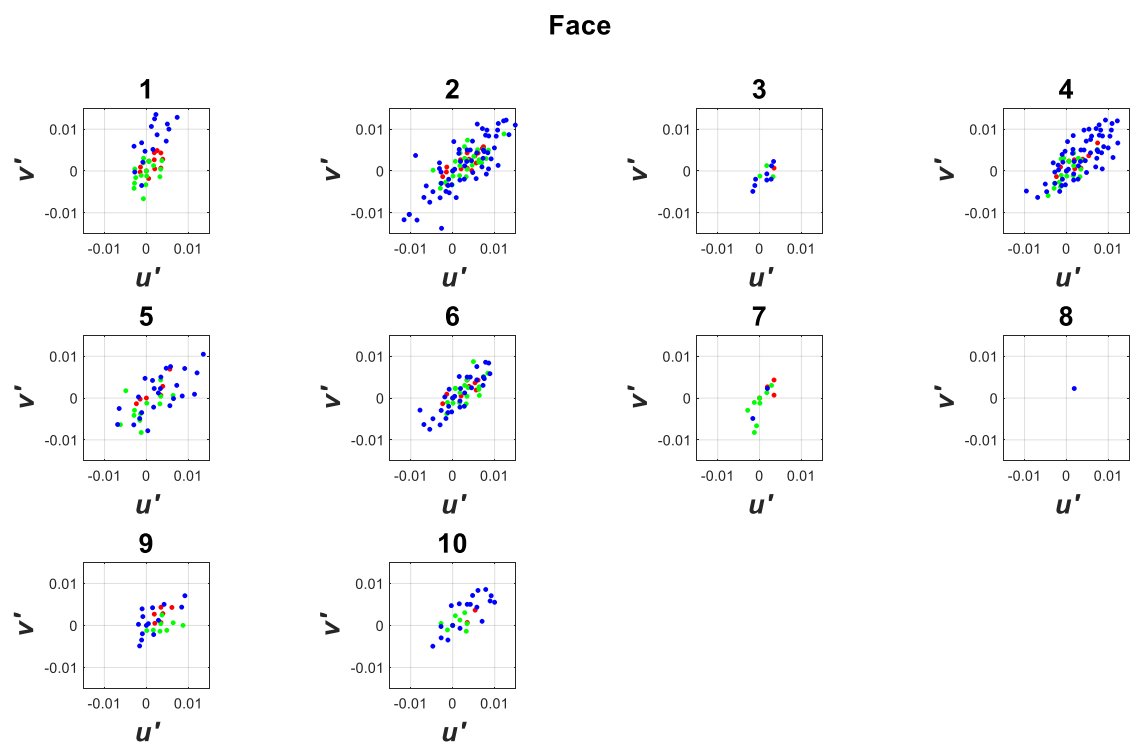


Figure 7-34 Test stimuli judged as “no difference” for face stimuli under D65 in the CIE 1976 $u'v'$ chromaticity diagram, following the same symbol conventions as in Figure 7-32.

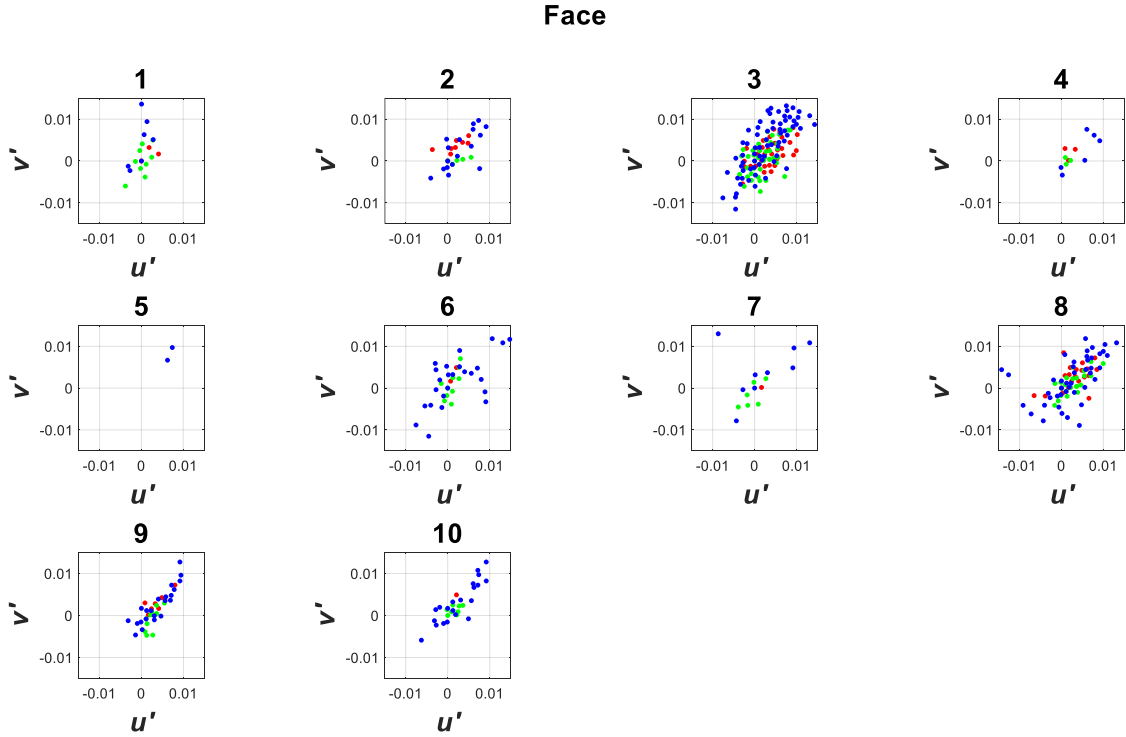


Figure 7-35 Test stimuli judged as “no difference” for face stimuli under D95 in the CIE 1976 $u'v'$ chromaticity diagram, following the same symbol conventions as in Figure 7-32.

As illustrated in Figure 7-32, under the D65 condition, observers 3, 8, and 9 reported only a small number of “no difference” judgments, and these points were not closely clustered around the reference stimulus. These response patterns indicate potential unreliability, and these observers were excluded from further analysis. Under the D95 condition (Figure 7-33), observers 2, 4, and 5 showed similar inconsistencies and were also excluded.

New ellipses were fitted based on the remaining data in both the $u'v'$ and CIELAB spaces, as shown in Figures 7-36 and 7-37, respectively. The corresponding ellipse parameters are summarized in Tables 7-10 and 7-11. In the $u'v'$ chromaticity diagram, the fitted ellipses after excluding unreliable observers largely preserved the original trends. The African skin color consistently showed the largest $\sqrt{ab}$ values, while Caucasian skin color showed the smallest, except for the face condition under D95, where the $\sqrt{ab}$ of Asian (0.0016) was slightly smaller than that of the Caucasian (0.0018).

These results continue to support the observation that lighter skin colors are associated with smaller JNCD. Regarding orientation, the ellipses remain more similar under the D65 (from 33.4° to 48.6° for face stimuli and from 40.5° to 51.3° for patch stimuli). In contrast, D95 conditions again show greater

variability (from 40.3° to 91.7° for face stimuli and from 21.8° to 91.1° for patch stimuli). The influence of stimulus type on ellipse orientation also remains more pronounced under D95, particularly for the Asian and African skin colors.

Table 7-10 Parameters of fitted ellipses after excluding unreliable observers in the CIE 1976 $u'v'$ chromaticity diagram.

White point	Ellipse	Race	Face				Patch			
			a	b	θ (°)	$\sqrt{ab}$	a	b	θ (°)	$\sqrt{ab}$
D65	1-SD	Caucasian	0.0030	0.0010	33.43	0.0017	0.0022	0.0008	40.46	0.0013
		Asian	0.0030	0.0013	44.63	0.0020	0.0029	0.0012	43.80	0.0019
		African	0.0058	0.0018	48.60	0.0032	0.0032	0.0019	51.27	0.0025
	3-SD	Caucasian	0.0091	0.0030	33.43	0.0052	0.0067	0.0024	40.46	0.0040
		Asian	0.0090	0.0038	44.63	0.0059	0.0086	0.0036	43.80	0.0056
		African	0.0175	0.0053	48.60	0.0096	0.0097	0.0058	51.27	0.0075
	95% confidence	Caucasian	0.0074	0.0025	33.43	0.0043	0.0055	0.0020	40.46	0.0033
		Asian	0.0074	0.0031	44.63	0.0048	0.0070	0.0029	43.80	0.0045
		African	0.0142	0.0043	48.60	0.0078	0.0079	0.0047	51.27	0.0061
D95	1-SD	Caucasian	0.0024	0.0013	91.66	0.0018	0.0018	0.0004	92.14	0.0009
		Asian	0.0025	0.0010	69.29	0.0016	0.0024	0.0013	33.97	0.0017
		African	0.0062	0.0010	40.29	0.0025	0.0040	0.0016	21.75	0.0026
	3-SD	Caucasian	0.0073	0.0039	91.66	0.0053	0.0054	0.0013	92.14	0.0027
		Asian	0.0076	0.0031	69.29	0.0049	0.0071	0.0038	33.97	0.0052
		African	0.0187	0.0029	40.29	0.0074	0.0121	0.0049	21.75	0.0077
	95% confidence	Caucasian	0.0059	0.0032	91.66	0.0044	0.0044	0.0011	92.14	0.0022
		Asian	0.0062	0.0025	69.29	0.0040	0.0058	0.0031	33.97	0.0043
		African	0.0153	0.0024	40.29	0.0060	0.0099	0.0040	21.75	0.0063

Excluding unreliable observers had a limited impact on the overall shape and orientation of the fitted ellipses. Under both D65 and D95 conditions, the orientation values remained largely stable, with differences below 24.7° for D65 and under 6.5° for D95. The general elliptical structures and major axis directions were preserved, indicating that the original perceptual patterns were robust. Minor changes were observed in ellipse size: under D65, the African skin color showed the most notable increase in $\sqrt{ab}$ (approximately 0.0011 for face and 0.0005 for patch), while other changes remained below 0.0003. Under D95, size changes were all below 0.0006.

In the CIELAB color space, the fitted ellipses after excluding unreliable observers also maintained the patterns observed before. For patch stimuli, a consistent size order was found under both D65 and D95

conditions: Asian > African > Caucasian. This stable pattern further supports the view that patch stimuli result in more reliable judgments than face stimuli. The orientation of the ellipses showed similar trends to those in the $u'v'$ chromaticity diagram. Under D65, the orientations of the three skin colors remained relatively close, while greater discrepancies were observed under D95. The influence of stimulus type on ellipse orientation also remained more pronounced under D95, particularly for Asian and African skin colors. These results indicate that the exclusion of low-reliability observers had minimal impact on the perceptual outcomes. The overall patterns in ellipse size, orientation, and stimulus-type dependency were preserved, confirming the robustness of the original results.

The larger variation observed in African skin color is primarily due to its lower luminance. The African stimuli shared the same hue angle and chroma as the Caucasian stimuli but had a much lower average luminance (approximately 6 cd/m^2 compared to 33 cd/m^2). The low luminance, limited by the display's dynamic range, reduced color discrimination and increased variability. This resulted from the design choice to maintain consistent relative lightness across skin colors.

Table 7-11 Parameters of fitted ellipses after excluding unreliable observers in the CIELAB a^*-b^* plane.

White point	Ellipse	Race	Face				Patch			
			a	b	θ (°)	$\sqrt{ab}$	a	b	θ (°)	$\sqrt{ab}$
D65	1-SD	Caucasian	1.76	0.73	54.89	1.13	1.34	0.55	67.09	0.86
		Asian	1.63	0.75	75.65	1.10	1.65	0.72	72.56	1.09
		African	2.19	0.68	76.98	1.22	1.23	0.68	89.59	0.92
	3-SD	Caucasian	5.28	2.19	54.89	3.40	4.02	1.66	67.09	2.58
		Asian	4.89	2.24	75.65	3.31	4.95	2.15	72.56	3.26
		African	6.58	2.03	76.98	3.66	3.70	2.04	89.59	2.75
	95% confidence	Caucasian	4.31	1.79	54.89	2.78	3.28	1.35	67.09	2.11
		Asian	3.99	1.82	75.65	2.70	4.04	1.76	72.56	2.66
		African	5.37	1.66	76.98	2.98	3.02	1.67	89.59	2.24
D95	1-SD	Caucasian	1.49	0.65	124.54	0.98	1.11	0.33	117.10	0.60
		Asian	1.20	0.56	99.67	0.82	1.13	0.79	59.15	0.94
		African	1.50	0.36	62.29	0.74	0.95	0.70	39.31	0.81
	3-SD	Caucasian	4.47	1.94	124.54	2.94	3.32	0.99	117.10	1.81
		Asian	3.59	1.68	99.67	2.46	3.38	2.37	59.15	2.83
		African	4.49	1.09	62.29	2.21	2.84	2.10	39.31	2.44
	95% confidence	Caucasian	3.65	1.58	124.54	2.40	2.71	0.80	117.10	1.48
		Asian	2.93	1.37	99.67	2.01	2.76	1.94	59.15	2.31
		African	3.66	0.89	62.29	1.80	2.32	1.71	39.31	1.99

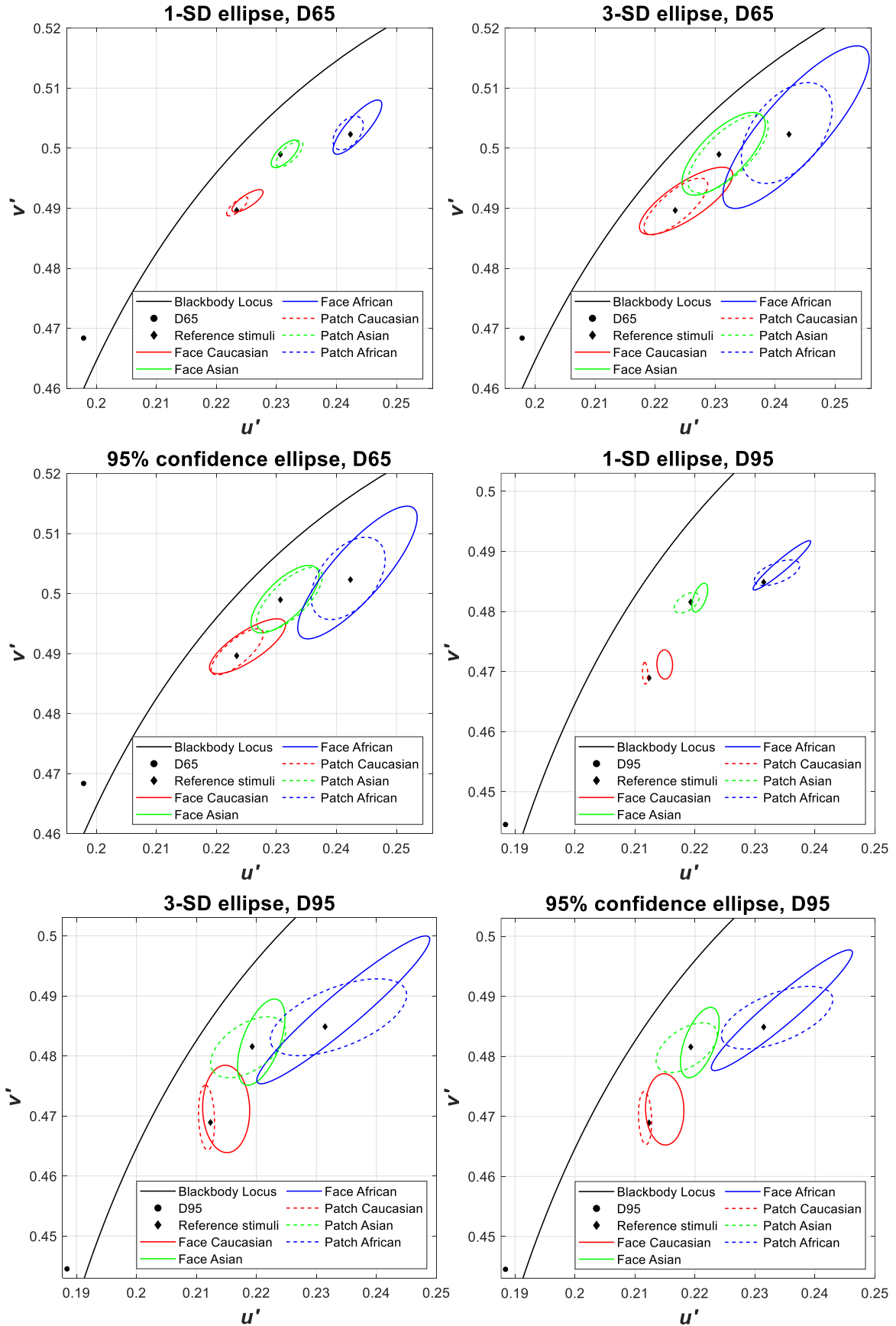


Figure 7-36 Fitted ellipses in the CIE 1976 $u'v'$ chromaticity diagram after excluding unreliable observers.

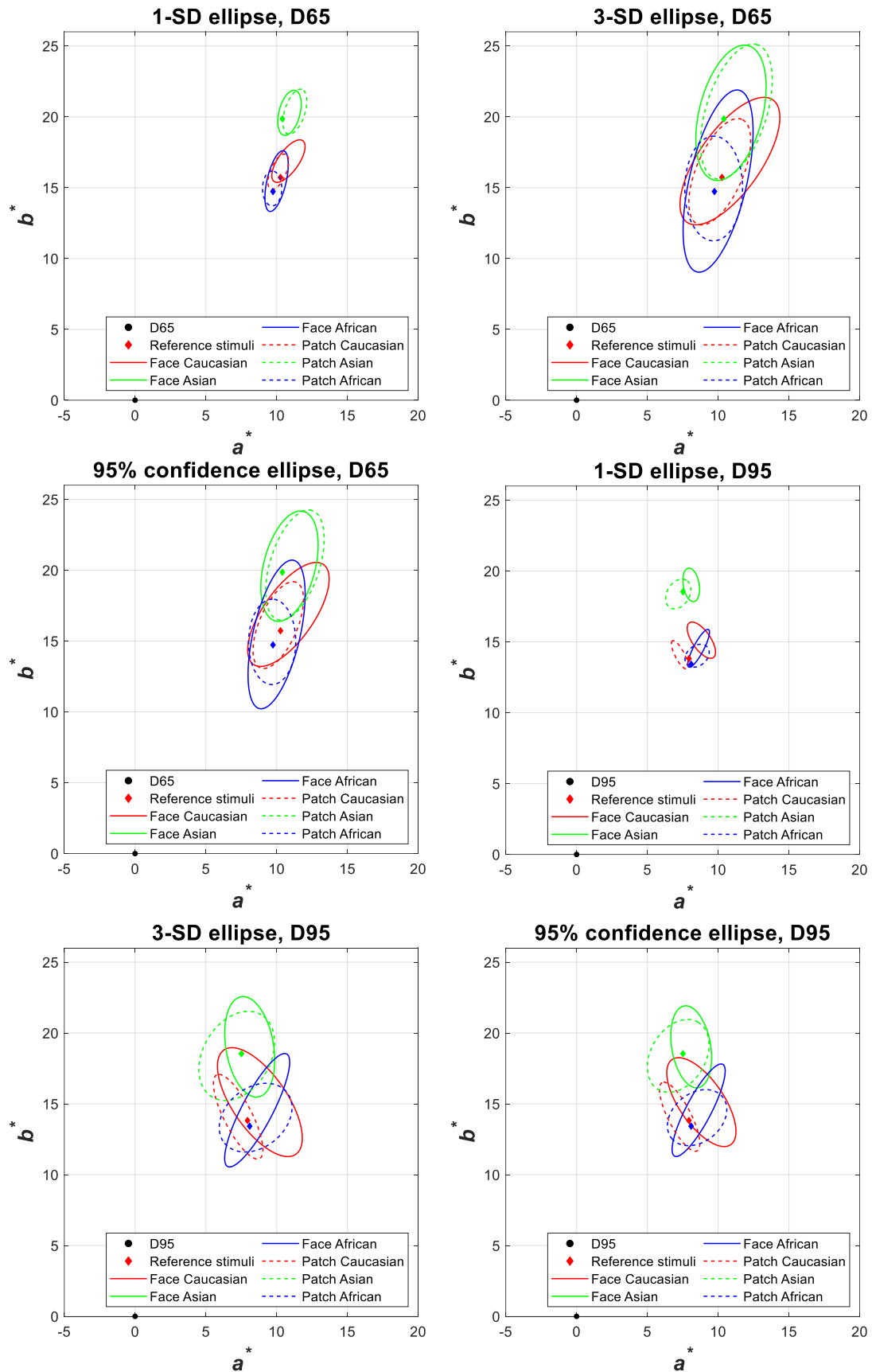


Figure 7-37 Fitted ellipses in the CIELAB a^* - b^* plane after excluding unreliable observers. The reference stimuli for each skin color are denoted by diamonds in the corresponding color.

7.5 Conclusion

Skin scales and skin models both serve as critical tools for characterizing skin color. Skin scales provide standardized references for classification and evaluation, while skin models enable the dynamic simulation of the optical and biological mechanisms of the skin tissue.

This chapter first reviewed and compared multiple representative skin scales in terms of their measurement methods, design purposes, and target populations. Their color distributions were analyzed in the CIELAB space, revealing differences in how skin tones are sampled and clustered across the scales. Furthermore, a skin model was constructed to simulate skin reflectance and predict skin color across several skin scales. Both Monte Carlo (MC) and Kubelka-Munk (KM) methods were implemented to simulate light propagation, with the KM method ultimately selected for further analysis due to its balance between computational efficiency and predictive accuracy. To further improve applicability, a look-up table (LUT) was generated based on optimized step settings, which can efficiently estimate reflectance from input LAB values.

An experiment was conducted to evaluate perceptual color differences under two display white points (D65 and D95), using both face and patch stimuli. Observers judged whether test stimuli differed perceptually from reference stimuli, enabling the construction of JNCD (Just Noticeable Color Difference) ellipses in both the CIE 1976 $u'v'$ diagram and CIELAB a^*-b^* plane. The results revealed consistent trends: darker skin colors exhibited larger JNCD ellipses, while lighter skin colors showed higher sensitivity to color differences. Stimulus type and adapting white point were also found to influence the orientation of JNCD ellipses. Under D95 adaptation, the orientation of JNCD ellipses varied more significantly across skin tones. Patch stimuli showed relatively consistent trends, whereas face stimuli resulted in more irregular patterns, particularly for Asian and African skin colors.

Through the analysis of skin scales and the skin model, LUT development, and psychophysical experiments, this study offers a foundation for skin color characterization, with implications for color calibration, digital rendering, and display optimization in skin-related applications.

Chapter 8 Conclusion

This thesis investigates the characterization and application of skin color, focusing on the development of color constancy algorithms, measurement techniques, and modeling approaches, while exploring the impact of adapting illumination on color perception.

The first study developed a color constancy algorithm using skin data in the cone contrast color space, designed for images with extensive skin regions. Reference gamut lookup tables were built from real skin reflectance spectra and light sources, and a loss function was designed to estimate illuminant chromaticities based on multiple gamut features. The method was validated through five-fold cross-validation on simulated skin RGB data and tested on fifty-five cropped facial images. Results showed consistently accurate illuminant estimations, outperforming existing algorithms. Performance benefited from the diversity of real light sources used in the reference gamut lookup tables. The algorithm remained robust when image pixels were limited but skin-dominated. Chapter 4 also examined the impact of camera spectral sensitivity (CSS), finding that CSS measurement errors caused larger angular errors than differences across similar camera models. In conclusion, this study demonstrated the feasibility of skin-based features in cone contrast space for illuminant estimation in skin-dominant images.

The second study explored how the joint effects of adapting and stimulus illuminance influence the perceived white point of displays when viewing image-based stimuli. Two experiments were conducted. Experiment I investigated perceived white points under forty-four adapting conditions, including six illuminance levels (30 to 15000 lx), seven CCTs (2500 to 10000 K), a dark condition, and an overcast condition, using full-screen images to simulate real usage. The chromaticities of the perceived display white points were generally distributed along the blackbody locus. A look-up table (LUT) was developed to map ambient conditions to corresponding white point CCTs. Experiment II validated the LUT with magnitude estimation, where observers rated image attributes including whiteness, comfort, naturalness, and preference. Images rendered using the proposed LUT received higher ratings than those from default settings on commercial smartphones, especially in whiteness under low CCT and low illuminance. Comfort, naturalness, and preference were strongly correlated,

particularly for skin images, highlighting the importance of accurate skin rendering. In summary, Chapter 5 determined and validated display white points across a broad range of adapting conditions, providing new insights into chromatic adaptation under practical applications.

The third study investigated the limitations of spectral skin color measurement and the challenges in accurate modeling. Motivated by the difficulty of acquiring comprehensive facial skin data due to skin's layered structure and instrument constraints, this study reviewed two primary techniques, spectrophotometers and spectroradiometers. Spectrophotometers were affected by aperture size and measurement pressure, while spectroradiometers were sensitive to measurement distance. Both methods were limited by small measurement areas and the inability to fully separate specular and diffuse reflectance, hindering accurate skin representation. This study also analyzed modeling strategies, beginning with common image capture setups and their applications. To balance complexity and computational cost, models often simplify skin layers or chromophore components, which may reduce accuracy. Deterministic models provide efficient simulations but rely on strong assumptions; nondeterministic models simulate photon behavior in detail but are computationally intensive. Chapter 6 highlighted these trade-offs and underscored the need for improved measurement tools and modeling methods to advance skin color characterization across practical and research contexts.

The fourth study aimed to integrate skin scales and skin models to establish a framework for skin color characterization. This study began with a systematic analysis of representative skin scales, examining their measurement methods, populations, and purposes. The color distributions of these scales in CIELAB space revealed notable differences in range and step size. A physically based skin model was established using the Monte Carlo (MC) and Kubelka-Munk (KM) methods. Evaluated using NIST data and skin scale data, the KM method showed lower color differences ΔE_{ab}^* across most scales and was selected for further use. A LUT was constructed using the KM model to estimate reflectance from scale data. A psychophysical experiment then estimated the just noticeable color differences (JNCD) using face and patch stimuli under D65 and D95. Results showed less stable adaptation under D95, with greater variability in JNCD ellipse orientation. Patch stimuli yielded more consistent results, and lighter skin colors showed smaller ellipses sizes. Null conditional analysis revealed unreliable judgments from some observers, especially under low luminance. By analyzing scatter plots of their

responses and excluding those with insufficient or dispersed data, the remaining ellipses retained original trends across conditions, confirming the robustness of the findings.

To summarize, this thesis has advanced the understanding and characterization of human skin color through a multidisciplinary approach, addressing key challenges in measurement, modeling, and application. By integrating biophysical knowledge, spectral reflectance data, and simulation techniques, it developed several novel tools and methods, including a color constancy algorithm used for images dominated by human skin, a LUT of the white point CCTs under different adapting illuminations, a physically based skin model, and a LUT for estimating skin reflectance. These contributions not only enhance the accuracy and efficiency of skin color characterization but also provide robust resources for future advancements in color science, dermatology, cosmetics, and imaging.

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