

High-to-Low Brightness Color Consistency Optimization for RGB LED Intelligent Lighting Based on Grassmann Color-Mixing Theory

Shumin Feng¹, Hao Chen², Shu Pan², Zongyuan Liu², Youqin Lin², and Weiming Lin^{1,*}

¹*School of Opto-Electronic and Communication Engineering, Xiamen University of Technology, Xiamen 361024, China*

²*Leedarson Lighting Group Corpocyclen Ltd, Zhangzhou 363900, China*

ABSTRACT: RGB LED luminaires often exhibit nonlinear luminous-flux variation and chromaticity-coordinate drift during high-to-low brightness switching, reducing color stability at low brightness levels. To address this problem, this paper proposes a color-stability-oriented RGB LED color-mixing optimization algorithm. Nonlinear fitting is first used to compensate for temperature-induced luminous-flux variation and chromaticity shift. Then, a spectral reconstruction method based on Bounded-Variable Least Squares (BVLS)-constrained parameter mapping is developed to predict RGB-channel spectra and correct single-channel chromaticity coordinates under different duty cycles. Furthermore, a two-dimensional affine chromaticity-point mapping method is introduced to adaptively correct the target chromaticity point according to the variation of RGB primary chromaticity coordinates at different brightness levels. The proposed method is evaluated using chromaticity tolerance, CAM16, and CAM16-UCS. Experimental results show that the chromaticity tolerance can be maintained within four SDCM steps in the 1%–10% low-brightness range, while color appearance differences are reduced under different brightness conditions. These results demonstrate that the proposed method improves the color stability and visual consistency of RGB LED luminaires.

1. INTRODUCTION

LED light sources have been widely used in indoor and outdoor lighting, displays, backlighting, and other fields due to their high luminous efficiency, tunable light color, fast response, and long service life [1]. In intelligent lighting systems, light sources must operate over a wide brightness range. When LEDs are switched from high-brightness to low-brightness operating points, variations in the driving current and junction temperature may alter the carrier distribution in the active region of the LED chip [2], the semiconductor bandgap, the electric field in the quantum wells, and the radiative recombination process. Consequently, the spectral power distribution (SPD) of the LED is often no longer a simple linear scaling in amplitude, and spectral deformation, such as peak-wavelength shifts, spectral broadening, and tail variations, may also occur [3, 4]. In particular, under low-brightness conditions, the driving current is further reduced, making the luminescent characteristics of LEDs more sensitive to current variations and thermal effects. As a result, the deviation of the spectral profile is usually more pronounced, ultimately leading to perceptible color differences in LED luminaires under different brightness conditions [5].

To address the issue of color stability between high- and low-brightness states, several categories of approaches have been developed in existing studies. The first category is lookup-table and empirical compensation methods, in which output data are sampled at different brightness levels, and mapping

relationships are established. During operation, correction is performed by lookup or interpolation according to the operating point. In [6], polynomial fitting was used to compensate for chromaticity drift generated during the dimming process of an RGB LED projector. Such methods are simple to implement, but their robustness against device batch variations, aging, and environmental changes is limited. The second category is closed-loop color control. In this approach, color or spectral sensors are introduced to form a feedback loop, and color drift caused by temperature, aging, or external disturbances is compensated online through control algorithms. In [7], a multichannel spectral sensor, a proportional-integral (PI) controller, and an optimization algorithm were employed to maintain the target chromaticity or correlated color temperature (CCT) under external light disturbance and LED spectral drift. However, additional sensors and feedback links are required in such methods, which increases system cost, complexity, and deployment difficulty. The third category is state-variable-based model compensation. In this approach, state variables highly correlated with spectral and chromaticity parameters, such as duty cycle and temperature, are selected, and predictive models from state variables to color drift are established. In [8], a temperature-spectral power distribution model was established and combined with NSGA-II (Non-dominated Sorting Genetic Algorithm II) to compensate for color-mixing results. In [9], Li et al. developed a junction-temperature prediction model for white LEDs based on ambient temperature, driving current, and spectral characteristic parameters. Such methods can reduce dependence on optical sensors and offer advantages, such as low

* Corresponding author: Weiming Lin (linwm@xmut.edu.cn).

cost, easy integration, and suitability for embedding in color-mixing control algorithms. In addition, since the model inputs can be directly obtained from the driving and control system, and the prediction relationships can be readily parameterized, these methods can be more easily incorporated into LED color-mixing algorithm frameworks for color optimization and control.

To address nonlinear luminous flux variation and chromaticity coordinate drift caused by temperature and current variations during high- and low-brightness switching of LED luminaires, an RGB LED color-mixing optimization framework oriented toward color stability is constructed in this study. Temperature correction and current compensation mechanisms are introduced, respectively, in this framework. Specifically, for chromaticity coordinate drift and luminous flux variation caused by temperature changes, a nonlinear fitting method is adopted for basic compensation. For variations in LED spectral profiles and single-channel chromaticity coordinate drift caused by driving current changes, as well as the resulting changes in the RGB primary-color gamut triangle and the mismatch in color-mixing geometric relationships, an LED spectral reconstruction method based on BVLS-constrained parameter mapping and a two-dimensional affine matrix color-point mapping method are proposed. Through these methods, progressive compensation from single-channel spectral reconstruction to composite color-point correction is achieved.

(1) An LED spectral reconstruction method based on BVLS-constrained parameter mapping is proposed. To address the chromaticity coordinate drift caused by variations in the driving current, the spectral power distribution of LEDs is taken as the starting point, and parameterized spectral functions are used to describe spectral profiles of the RGB channels under different duty-cycle conditions. Furthermore, BVLS is introduced into the constrained solution process of the spectral model parameters. A mapping relationship between the model parameters and the duty cycle is then established, thereby enabling the prediction and reconstruction of LED spectra at arbitrary target duty cycles and providing a basis for subsequent single-channel chromaticity coordinate calibration.

(2) A composite color-point correction method based on two-dimensional affine color-point mapping is proposed. To address the problem that the chromaticity coordinates of RGB primaries drift to different degrees under different brightness conditions, resulting in overall deformation of the gamut triangle and a mismatch between the original target color point and the current color-mixing geometric relationship, a two-dimensional affine transformation matrix is introduced on the basis of the spectral-parameterization model used to obtain the RGB primary chromaticity coordinates at the current brightness level. The target color point at the reference brightness is synchronously mapped into the RGB gamut triangle corresponding to the current brightness, so that the relative geometric position of the target color point within the RGB gamut triangle is maintained. In this way, the corrected target color point can better conform to the actual color-mixing relationship under the current brightness condition.

2. METHODS

As shown in Fig. 1, the RGB LED color control and calibration process is presented, in which the dashed box on the right represents the LED calibration module proposed in this study. This module is designed to address the luminous flux nonlinearity and chromaticity coordinate drift that occur during LED dimming. Finally, the calibrated control signals are obtained by integrating nonlinear calibration, spectral-parameter prediction, and color-point mapping correction. Through this process, the deviation between the actual composite color point and the target color point can be effectively reduced, and the color stability of the RGB LEDs under different brightness conditions can be improved.

2.1. Nonlinear Calibration of Brightness Influenced by Temperature

Temperature is one of the important factors affecting optical and chromatic characteristics of LEDs. As temperature increases, the emission peak of an LED usually shifts toward longer wavelengths, and the spectral power distribution changes accordingly, resulting in chromaticity-coordinate drift and luminous-flux variation, as shown in Fig. 2. For RGB or multi-channel color-mixing systems, LED chips of different colors exhibit different temperature sensitivities. Therefore, temperature disturbances may alter the relative luminous contribution of each channel, causing the composite color point and output luminous flux to deviate from their target values. To reduce the influence of temperature variation on chromaticity coordinates and luminous flux, nonlinear fitting is adopted in this paper for temperature compensation [10, 11]. The luminous-flux calibration process is expressed in Eqs. (1)–(3), and the chromaticity-coordinate calibration process is expressed in Eqs. (4)–(9).

$$Y_R = -0.003T_R^2 + 0.649T_R + 38.341 \quad (1)$$

$$Y_G = -0.0084T_G^2 + 4.0056T_G - 303.86 \quad (2)$$

$$Y_B = 0.0003T_B^2 - 0.0228T_B + 22.11 \quad (3)$$

$$x_R = -2 \times 10^{-7}T_R^2 + 0.0001T_R + 0.6719 \quad (4)$$

$$y_R = -5 \times 10^{-8}T_R^2 + 6 \times 10^{-5}T_R - 0.2974 \quad (5)$$

$$x_G = -2 \times 10^{-7}T_G^2 + 0.0002T_G + 0.1909 \quad (6)$$

$$y_G = -3 \times 10^{-6}T_G^2 + 0.0015T_G - 0.4043 \quad (7)$$

$$x_B = -2 \times 10^{-8}T_B^2 - 5 \times 10^{-5}T_B + 0.1671 \quad (8)$$

$$y_B = -2 \times 10^{-7}T_B^2 - 5 \times 10^{-5}T_B + 0.0255 \quad (9)$$

2.2. Grassmann's Law of Color Mixing

In 2021, Tang et al. [12] proposed a theory in which digital signals can be directly encoded and decoded into a uniform CIE 1931 xyY color space. It further indicates that a strict one-to-one relationship exists between the duty cycle of each binary pulse and the color component of the mixed light. During the encoding process, the digital pulses of multiple LED driving channels are converted into a unique coordinate (x_m, y_m, Y_m) in the CIE 1931 xyY color space, where (x_m, y_m) denotes the chromaticity coordinates of the mixed light, and Y_m denotes the luminous flux. According to Hermann Grassmann's law,

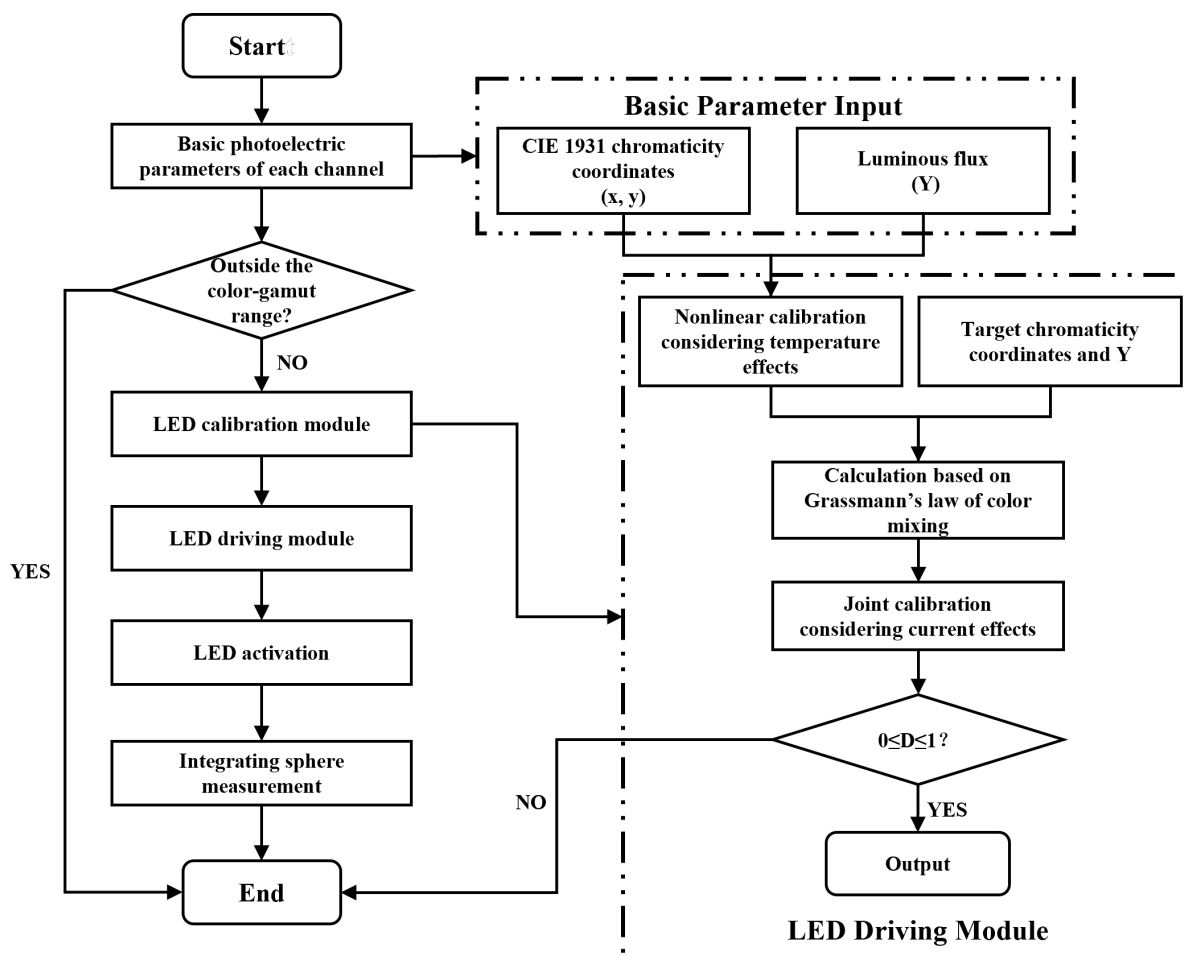


FIGURE 1. The framework of the proposed high-to-low brightness color consistency optimization method for RGB LED intelligent lighting.

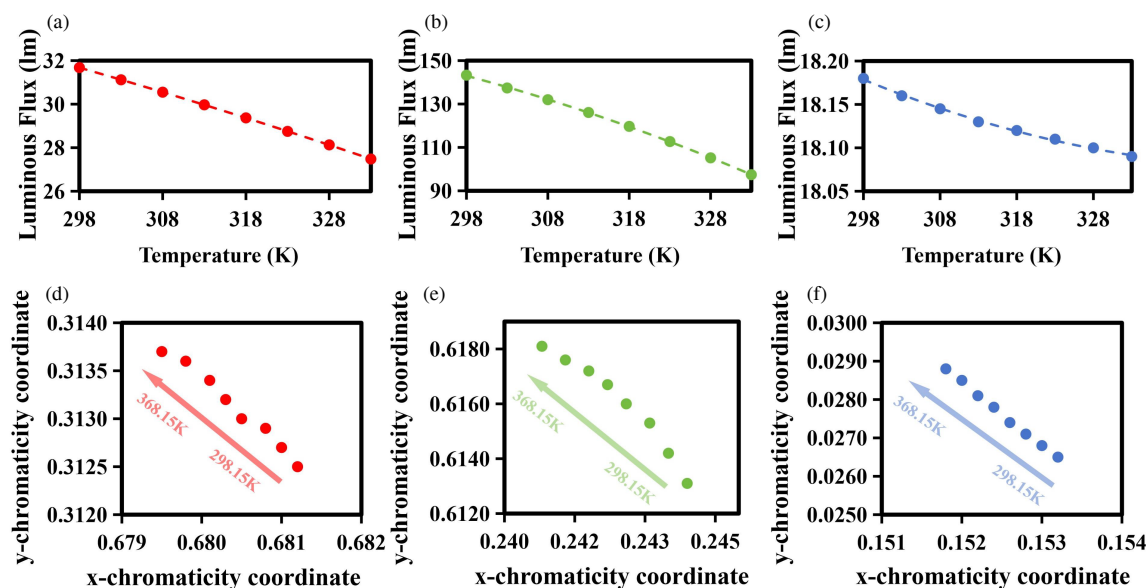


FIGURE 2. Influence of temperature on the chromaticity coordinates and luminous flux of RGB LED channels. (a) Luminous flux of the R channel, (b) luminous flux of the G channel, (c) luminous flux of the B channel, (d) chromaticity coordinates of the R channel, (e) chromaticity coordinates of the G channel, and (f) chromaticity coordinates of the B channel.

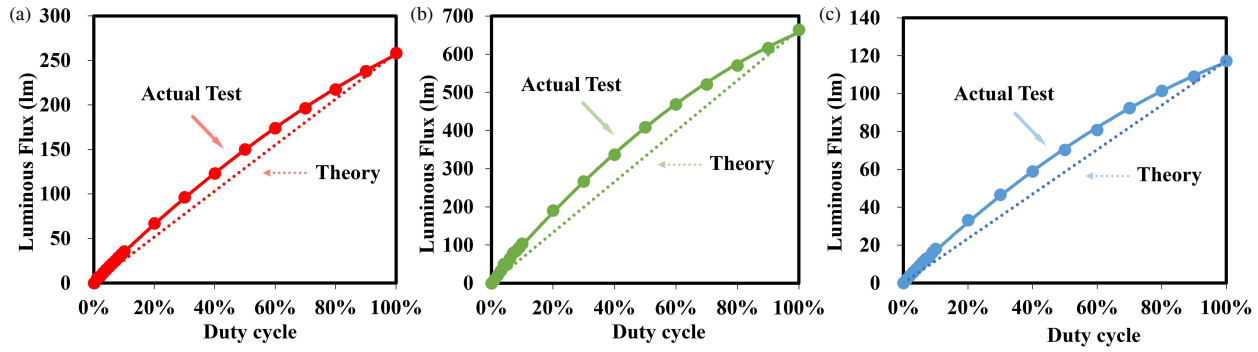


FIGURE 3. Basic assumptions of the Grassmann color-mixing equations and the actual nonlinear luminous-flux characteristics of LEDs. (a) Luminous flux of the R channel, (b) luminous flux of the G channel, and (c) luminous flux of the B channel.

the coordinates of mixed light can be calculated as follows:

$$x_m = \frac{\sum_{i=1}^n R_i x_i D_i}{\sum_{i=1}^n R_i D_i} \quad (10)$$

$$y_m = \frac{\sum_{i=1}^n R_i y_i D_i}{\sum_{i=1}^n R_i D_i} \quad (11)$$

Here, the digital pulses can be represented by a duty-cycle vector $D = (D_1, D_2, \dots, D_i, \dots, D_n)$, where D_i denotes the duty cycle of the i -th primary color, and n denotes the number of primary colors participating in color mixing. In addition, $R_i = Y_i/y_i$ represents the tristimulus-value sum of each LED channel under the specified current condition, and Y_i is the maximum luminous flux of a single LED channel at a 100% duty cycle.

During decoding, the duty cycle of each primary color is inversely derived from the coordinates of the mixed light in the CIE 1931 xyY color space. When $n = 3$, that is, in the case of three-primary-color mixing, three equations are constructed, and their unique solution can be expressed as follows:

$$\begin{cases} D_1 = \left[\frac{(y_2 - y_3)(x_3 - x_m) + (y_m - y_3)(x_2 - x_3)}{(y_2 - y_3)(x_3 - x_1) + (y_1 - y_3)(x_2 - x_3)} \right] \frac{y_1 Y_m}{y Y_1} \\ D_2 = \left[\frac{(y_3 - y_1)(x_1 - x_m) + (y_m - y_1)(x_3 - x_1)}{(y_3 - y_1)(x_1 - x_2) + (y_2 - y_1)(x_3 - x_1)} \right] \frac{y_2 Y_m}{y Y_2} \\ D_3 = \left[\frac{(y_2 - y_1)(x_1 - x_m) + (y_m - y_1)(x_2 - x_1)}{(y_2 - y_1)(x_1 - x_3) + (y_3 - y_1)(x_2 - x_1)} \right] \frac{y_3 Y_m}{y Y_3} \end{cases} \quad (12)$$

The luminous flux and chromaticity coordinates were corrected according to the temperature compensation functions, and the luminous flux and chromaticity coordinates under the current temperature conditions were obtained. Subsequently, the corrected chromaticity coordinates and luminous flux, together with the target composite color point (x_m, y_m) and target luminous flux Y_m , were substituted into the above Grassmann color-mixing equations for solution. Thus, the duty cycles required for each RGB channel under the current temperature condition can be derived.

2.3. Joint Calibration Affected by Current Factors

As indicated in Subsection 2.2, the theoretical color-mixing equations are generally established based on linear assumptions. However, certain limitations exist in practical RGB LED color mixing. On the one hand, the theoretical equations assume that the luminous flux of each channel is proportional to the duty cycle. In practice, LEDs are affected by injection efficiency, efficiency droop, self-heating, and other factors, and the luminous flux does not vary strictly linearly with the duty cycle [13], especially in the low-brightness region. However, the theoretical equations usually assume that the chromaticity coordinates (x_i, y_i) of each channel remain unchanged under different driving conditions, but variations in the actual driving current may cause changes in the spectral power distribution, peak wavelength, and full width at half maximum, thereby leading to a chromaticity-coordinate drift of the RGB primaries. Therefore, if fixed luminous-flux ratios and fixed primary chromaticity coordinates are directly used for color-mixing calculations, the actual output characteristics under different brightness conditions cannot be accurately described, and deviations in the composite color point are likely to occur [14].

2.3.1. Nonlinear Calibration of Luminous Flux

To address the problem that luminous flux does not vary strictly linearly with the duty cycle, nonlinear fitting was adopted in this study to calibrate the luminous flux. By establishing a nonlinear mapping relationship between the duty cycle and the actual luminous flux, as shown in Fig. 3, the theoretical duty cycle calculated using the color-mixing equations in Section 2.2 was corrected [15, 16]. The correction functions are expressed in Eqs. (13)–(15). After calibration, a duty cycle that better matches the actual output characteristics can be obtained, thereby reducing the influence of luminous flux nonlinearity on color mixing accuracy.

$$Y_R = -81.541D_R^2 + 336.23D_R + 1.8711 \quad (13)$$

$$Y_G = -302.26D_G^2 + 952.24D_G + 6.8305 \quad (14)$$

$$Y_B = -48.668D_B^2 + 164.43D_B + 1.0575 \quad (15)$$

2.3.2. Spectral Modeling and Prediction

To characterize the spectral variation of the RGB LEDs under different duty-cycle conditions, this study performs single-channel spectral parameterization based on the Bridgelux® SMD 3838 RGBW LED chip [17]. Fig. 4 shows the normalized spectra of the RGB LED used in this study at a 100% duty cycle. For the red and green LED channels, the measured spectra exhibit a certain degree of asymmetry [18]. Therefore, the Exponentially Modified Gaussian (EMG) function was adopted to describe their spectral profiles:

$$S(\lambda) = y_0 + \frac{A}{t_0} \exp \left[\frac{1}{2} \left(\frac{w}{t_0} \right)^2 - \frac{\lambda - x_c}{t_0} \right] \cdot \frac{1}{2} \left[1 + \operatorname{erf} \left(\frac{1}{\sqrt{2}} \left(\frac{\lambda - x_c}{w} - \frac{w}{t_0} \right) \right) \right] \quad (16)$$

where λ is the wavelength, $S(\lambda)$ is the spectral intensity, y_0 is the baseline term, A the intensity scaling factor, x_c the central wavelength, w the peak-width parameter, and t_0 the spectral asymmetry parameter.

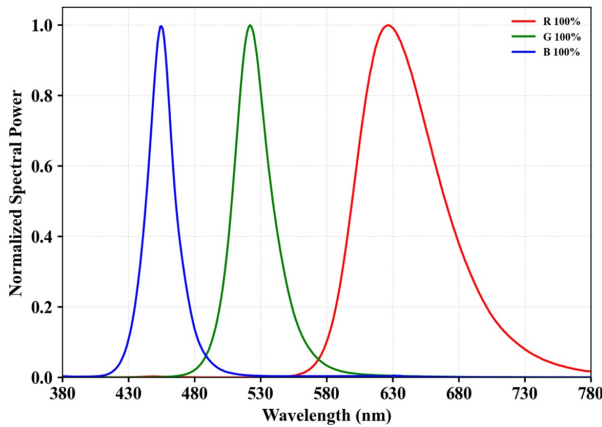


FIGURE 4. Normalized spectra of the R, G, and B channels at 100% duty cycle.

In contrast, the blue LED used in this study exhibits a narrow dominant peak, together with a slight shoulder or tailing feature on the long-wavelength side. A single function is difficult to accurately describe both the main peak and local shoulder feature. Therefore, a dual-peak model consisting of a Voigt main peak and a Gaussian shoulder peak is adopted to model the blue channel [25]:

$$S(\lambda) = y_0 + A_1 V(\lambda; x_{c1}, w_{G1}, w_{L1}) + A_2 G(\lambda; \mu_2, w_{G2}) \quad (17)$$

where y_0 denotes the baseline term; $V(\cdot)$ represents the Voigt function, which is used to describe the blue main peak; $G(\cdot)$ denotes the Gaussian function, which is used to describe the blue shoulder peak; A_1 and A_2 are the intensity scaling factors of the main and shoulder peaks, respectively; x_c and μ_2 represent the center wavelengths of the main and shoulder peaks, respectively; w_{G1} , w_{L1} , and w_{G2} are the corresponding width parameters.

To account for the variations in the LED spectral parameters induced by the duty cycle, an LED spectral reconstruction method based on BVLS-constrained parameter mapping is proposed in this study. The proposed method mainly consists of two stages: modeling and prediction, as shown in Fig. 5.

In the modeling stage, the measured spectra $S(\lambda, D)$ of the RGB channels are first collected under different duty cycles D . Parameterized fitting is then performed using Eqs. (17) and (18), and the corresponding model parameter vector $\theta = (A, \mu, \sigma, \dots)$ is obtained. Subsequently, least-squares linear regression was adopted to describe the variation relationship between each model parameter and the duty cycle. For the i -th model parameter of channel c , it is expressed as

$$\theta_{c,i}(D) = k_{c,i}D + b_{c,i} \quad (18)$$

where $c \in \{R, G, B\}$ denotes the LED channel; $\theta_{c,i}(D)$ represents the i -th model parameter of channel c at duty cycle D ; $k_{c,i}$ and $b_{c,i}$ denote the regression slope and intercept of this parameter with respect to duty cycle D , respectively. For N duty-cycle sampling points $D_1, D_2, \dots, D_N$, $k_{c,i}$ and $b_{c,i}$ are obtained by minimizing the squared error between the measured and fitted parameters as follows:

$$\min_{k_{c,i}, b_{c,i}} \sum_{n=1}^N [\theta_{c,i,n} - (k_{c,i}D_n + b_{c,i})]^2 \quad (19)$$

Furthermore, the relationship between the model parameters of the RGB channels and the duty cycle can be expressed as follows:

$$\begin{cases} \theta_R(D) = K_R D + B_R \\ \theta_G(D) = K_G D + B_G \\ \theta_B(D) = K_B D + B_B \end{cases} \quad (20)$$

where $\theta_R(D)$, $\theta_G(D)$, and $\theta_B(D)$ denote the model parameter vectors of the R, G, and B channels at duty cycle D , respectively; K_R , K_G , and K_B are the slope vectors of the corresponding channels; B_R , B_G , and B_B are the intercept vectors of the corresponding channels. Because R and G channels are modeled using the EMG function, whereas the B channel is modeled using the Voigt-Gaussian dual-peak model, the parameter vectors of the three channels are defined as

$$\theta_R(D) = [y_0(D), A(D), x_c(D), w(D), t_0(D)]^T \quad (21)$$

$$\theta_G(D) = [y_0(D), A(D), x_c(D), w(D), t_0(D)]^T \quad (22)$$

$$\theta_B(D) = [y_0(D), A_1(D), x_{c1}(D), w_{G1}(D), w_{L1}(D), A_2(D), \mu_2(D), w_{G2}(D)]^T \quad (23)$$

Measured spectra of each RGB channel were collected under 19 duty-cycle conditions, including 1%–10%, 20%, 30%, 40%, 55%, 60%, 70%, 80%, 90%, and 100%. The spectrum at each duty cycle was then fitted using a parameterized spectral model. Subsequently, with the duty cycle as the independent variable and the spectral model parameters of each channel as dependent variables, different models were established. The mean Train NRMSE, LOOCV NRMSE, LOOCV R^2 , and number of coefficients were used to evaluate the fitting error, generalization performance, and model complexity. As shown in Table 1, the training error generally decreased as the model order increased. However, higher-order models were more sensitive to the training samples and local data fluctuations, which may

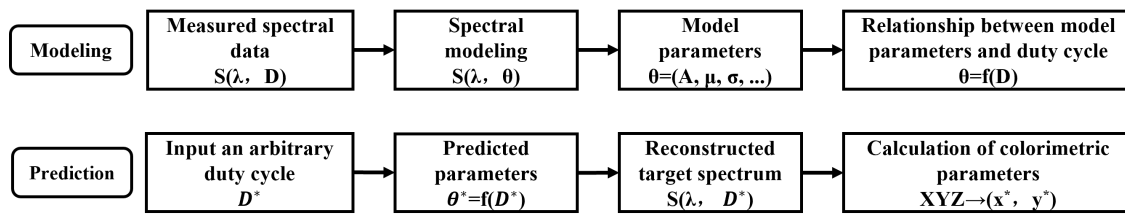


FIGURE 5. Spectral parameterization modeling and prediction method based on model-parameter regression.

TABLE 1. Comparison of fitting accuracy, generalization performance, and complexity of different models.

Model	Train NRMSE	LOOCV NRMSE	LOOCV R^2	Coeff.
Linear	0.1212	0.1407	0.6980	2
Quadratic	0.1167	0.1364	0.7054	3
Cubic	0.0952	0.1359	0.6996	4
Poly-5	0.0653	0.1084	0.8237	6
Poly-7	0.0575	0.3288	-0.7802	8

TABLE 2. Prediction risk assessment results of different models in the low-duty-cycle range.

Model	Channel	Parameter	Low-Duty Overshoot Ratio	Risk Type
Linear	/	/	/	No risk
Quadratic	G	y_0	1.219	enlarged variation in low-duty prediction
	B	y_0	1.868	significantly enlarged variation in low-duty prediction
Cubic	R	y_0	1.115	enlarged variation in low-duty prediction
	R	A_c	1.127	enlarged variation in low-duty prediction
	G	y_0	1.126	enlarged variation in low-duty prediction
	G	A_c	1.104	enlarged variation in low-duty prediction
Poly-5	B	x_{c1}	1.111	out-of-range prediction
	B	w_{G1}	1.150	out-of-range prediction
	B	w_{G2}	1.235	out-of-range prediction
Poly-7	B	x_{c1}	1.054	out-of-range prediction
	B	w_{G2}	1.093	out-of-range prediction

lead to overfitting. For example, although the Poly-7 model achieved a relatively low Train NRMSE, its LOOCV NRMSE increased significantly, and its LOOCV R^2 became negative, indicating that the high-order nonlinear model had poor predictive capability for samples not involved in model fitting.

Considering the prediction stability in the low-duty-cycle range of 1%–10%, densely spaced low-duty-cycle verification points were further generated with a step size of 0.1%. These points were then substituted into models of different orders to obtain the corresponding predicted parameter values. Subsequently, the predicted range was compared with the measured range, and the Low-Duty Overshoot Ratio was calculated to characterize the amplification degree of the predicted variation relative to the measured variation. In addition, the Risk Type was determined according to whether the predicted values exceeded the reasonable range of the measured parameters. As shown in Table 2, the Low-Duty Overshoot Ratio of the Quadratic and Cubic models was greater than 1 for some parameters, indicating that their predicted variation amplitudes in the

low-duty-cycle range exceeded the measured variation amplitudes and thus presented a risk of prediction amplification. For the Poly-5 and Poly-7 models, out-of-range predictions were observed for some parameters of the B channel, suggesting that the high-order models may introduce non-physical parameter fluctuations and unstable prediction results. In contrast, no prediction amplification or out-of-range risk was observed for the Linear model, indicating that it exhibited better prediction stability in the low-duty-cycle range.

Considering the fitting error, generalization performance, model complexity, and prediction stability in the low-duty-cycle range, the Linear model was finally adopted in this study to describe the relationship between the duty cycle and spectral model parameters. Least-squares linear regression was performed using the NumPy package in Python, and the slope and intercept vectors of the model parameters for each channel with respect to the duty cycle were obtained as follows:

$$\mathbf{K}_R = [-0.0576, 1557.0889, 0.0101, 0.3421, 0.5923]^T \quad (24)$$

$$\mathbf{B}_R = [-0.0026, 49.4831, 609.0029, 19.0741, 36.3769]^T \quad (25)$$

$$K_G = [0.1405, 1293.3392, -8.9842, 0.9523, -1.0109]^T \quad (26)$$

$$B_G = [0.0043, 53.5050, 520.8351, 9.7099, 14.6677]^T \quad (27)$$

$$K_B = [0.1260, 1700.1370, -6.3929, 11.7784, -1.5450, 746.0944, -11.3391, -7.0001]^T \quad (28)$$

$$B_B = [-0.0028, 38.1249, 462.0390, 22.1211, 4.7631, 15.9765, 463.3360, 23.0981]^T \quad (29)$$

Therefore, for any target duty cycle D^* , the predicted model parameters of the corresponding channel can be calculated according to the above relationship:

$$\theta_c(D^*) = K_c D^* + B_c \quad (30)$$

Then, the predicted parameters $\theta_c(D^*)$ are substituted into the spectral model of the corresponding channel, and the reconstructed spectrum at the target duty cycle is obtained:

$$S_c(\lambda, D^*) = f_c[\lambda; \theta_c(D^*)] \quad (31)$$

where $S_c(\lambda, D^*)$ denotes the reconstructed spectrum of channel c at the target duty cycle D^* , and $f_c(\cdot)$ denotes the parameterized spectral function corresponding to this channel. Through this method, the influence of duty-cycle variation on the LED spectral profile can be transformed into variations in model parameters, thereby enabling the prediction and reconstruction of LED spectra under different duty-cycle conditions.

2.3.3. Chromaticity Affine Mapping

Considering that the chromaticity coordinates of the RGB primaries drift under different brightness conditions, the RGB gamut triangle at the current brightness level may not be completely consistent with that at the reference brightness level, as illustrated in Fig. 6. If the target color point at the reference brightness level is still directly used for the color-mixing calculation, the geometric relationship between the target color point and current RGB primaries may be shifted, thereby affecting the accuracy of the composite color point.

To address this issue, a two-dimensional affine color-point mapping method is introduced in this study based on the corrected single-channel chromaticity coordinates obtained from spectral modeling. In this method, the target color point at the reference brightness level is synchronously mapped into the RGB gamut triangle corresponding to the current brightness level, so that the corrected target color point can better conform to the actual color-mixing geometric relationship under the current brightness condition.

Specifically, the chromaticity coordinates of the RGB primary-color points were first measured under the high-brightness reference condition and denoted as $R(x_R, y_R)$, $G(x_G, y_G)$, and $B(x_B, y_B)$, respectively. These points were used as the three vertices of the reference RGB gamut triangle. On this basis, the corrected chromaticity coordinates of the RGB primaries under the current brightness condition were obtained according to the aforementioned spectral reconstruction method and denoted as $R'(x'_R, y'_R)$, $G'(x'_G, y'_G)$,

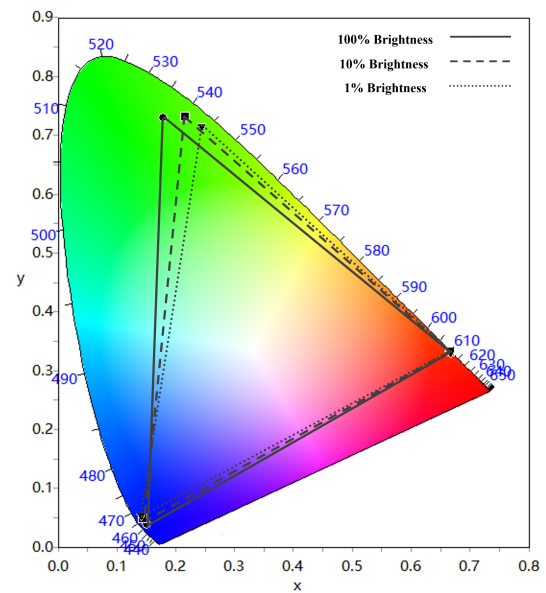


FIGURE 6. Gamut triangles at 100%, 10%, and 1% brightness levels.

and $B'(x'_B, y'_B)$, respectively. To describe the overall mapping relationship between the RGB gamut triangle in the reference state and that in the current state, the two groups of primary-color vertices are represented in a homogeneous coordinate form on the xy plane, and the following matrices are constructed:

$$P = \begin{bmatrix} x_R & x_G & x_B \\ y_R & y_G & y_B \\ 1 & 1 & 1 \end{bmatrix}, \quad P' = \begin{bmatrix} x'_R & x'_G & x'_B \\ y'_R & y'_G & y'_B \\ 1 & 1 & 1 \end{bmatrix} \quad (32)$$

A two-dimensional affine transformation can preserve the relative positional relationships among points, lines, and the interior of a triangle. Therefore, it can be used to describe the geometric mapping from the reference RGB gamut triangle to the current RGB gamut triangle. Let the affine transformation matrix be $A \in \mathbb{R}^{3 \times 3}$. Then, the primary-color vertices in the reference and current states satisfy

$$P' = AP \quad (33)$$

When the three primary-color points in the reference state are non-collinear, matrix P is invertible. Therefore, the affine transformation matrix can be expressed as:

$$A = P'P^{-1} \quad (34)$$

This matrix can be used to map any point in the RGB gamut triangle under the reference brightness condition to the RGB gamut triangle corresponding to the current brightness condition. For the target color point under the reference state:

$$m = \begin{bmatrix} x_m \\ y_m \\ 1 \end{bmatrix} \quad (35)$$

The corresponding corrected target color point under the current brightness condition can be expressed as $m' = Am$. By

further substituting Eq. (34), it can be obtained that

$$\begin{bmatrix} x'_m \\ y'_m \\ 1 \end{bmatrix} = \begin{bmatrix} x'_R & x'_G & x'_B \\ y'_R & y'_G & y'_B \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} x_R & x_G & x_B \\ y_R & y_G & y_B \\ 1 & 1 & 1 \end{bmatrix}^{-1} \begin{bmatrix} x_m \\ y_m \\ 1 \end{bmatrix} \quad (36)$$

Thus, the corrected target chromaticity coordinates (x'_m, y'_m) under the current brightness condition can be obtained as follows: By synchronously mapping the target color point, this method preserves the relative geometric position of the target point within an RGB triangle. To a certain extent, the influence of primary-color point drift on the color-mixing result under low-brightness conditions can be compensated, and color consistency under different brightness conditions can be improved.

3. RESULTS

3.1. Experimental Conditions

The Bridgelux® SMD 3838 RGBW LED chip was used in this experiment. Only the three colored-light channels were employed in the experiment. The optical parameters of the light source are listed in Table 3, and all parameters were measured at a temperature of 25 °C under a duty cycle of 100%. For subsequent analysis, the duty-cycle range of 1%–10% was defined as the low-brightness range, whereas the range of 10%–100% was defined as the high-brightness range.

TABLE 3. Optical parameter information of the four LED chips.

LED	CIE1931- <i>x</i>	CIE1931- <i>y</i>	Luminous Flux (lm)
R	0.6659	0.3319	27.72
G	0.1786	0.7303	136.00
B	0.1515	0.0380	18.18
W	0.5226	0.4380	124.90

Figure 7 shows the positions of the 23 color points used in the experiment in the CIE 1931 *xyY* color space. The seven selected white-light color points are located near the Planckian locus and correspond to the reference color points with the corresponding correlated color temperatures. The 16 selected colored-light points are located near the three primaries of the LED light source and in the transitional regions between them. The detailed chromaticity coordinates are presented in Table 4.

Experiments were conducted using LED products supplied by Leedarson Ltd. Fig. 8 shows a schematic of the experimental test setup. The equipment used for testing included a YF1000 integrating sphere and an HAAS-2000 spectrometer manufactured by the Everfine Corporation.

3.2. Chromaticity Tolerance Evaluation

To evaluate the performance of the proposed algorithm, the chromaticity tolerance in the CIE 1976 *u'v'* color space was adopted as the evaluation metric. First, the CIE 1931 *xy* chromaticity coordinates were converted into the CIE 1976 *u'v'* chromaticity coordinates, and the conversion relationship is ex-

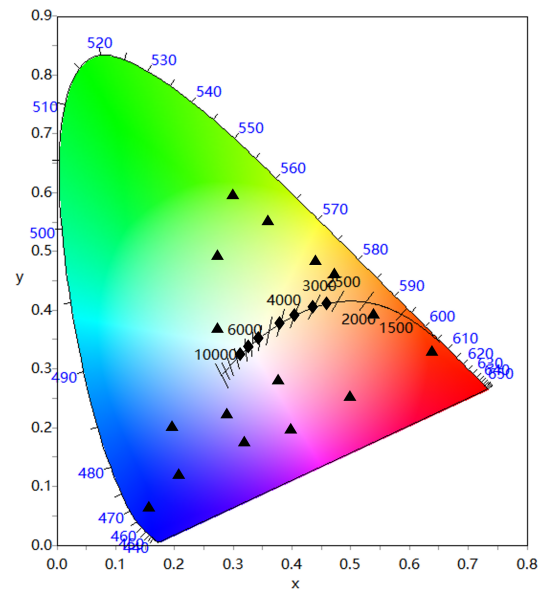


FIGURE 7. Distribution of the 23 test color points.

TABLE 4. Chromaticity coordinates of the 23 test color points.

Color Name	CIE1931- <i>x</i>	CIE1931- <i>y</i>
2700K	0.4593	0.4107
3000K	0.4366	0.4042
3500K	0.4053	0.3909
4000K	0.3805	0.3767
5000K	0.3450	0.3516
5700K	0.3280	0.3372
6500K	0.3135	0.3237
Warm Orange	0.5381	0.3903
Saturated Red	0.6376	0.3287
Deep Pink	0.4982	0.2519
Magenta	0.3965	0.1959
Light Pink	0.3749	0.2785
Saturated Pink	0.3187	0.1736
Light Purple	0.2895	0.2210
Violet	0.2054	0.1185
Deep Blue	0.1550	0.0631
Light Blue	0.1967	0.2004
Mint Green	0.2722	0.3669
Bright Green	0.2725	0.4915
Vivid Green	0.2982	0.5955
Lime Green	0.3593	0.5496
Golden Yellow	0.4398	0.4820
Amber	0.4711	0.4609

pressed as follows:

$$\begin{cases} u' = \frac{4x}{-2x + 12y + 3} \\ v' = \frac{9y}{-2x + 12y + 3} \end{cases} \quad (37)$$

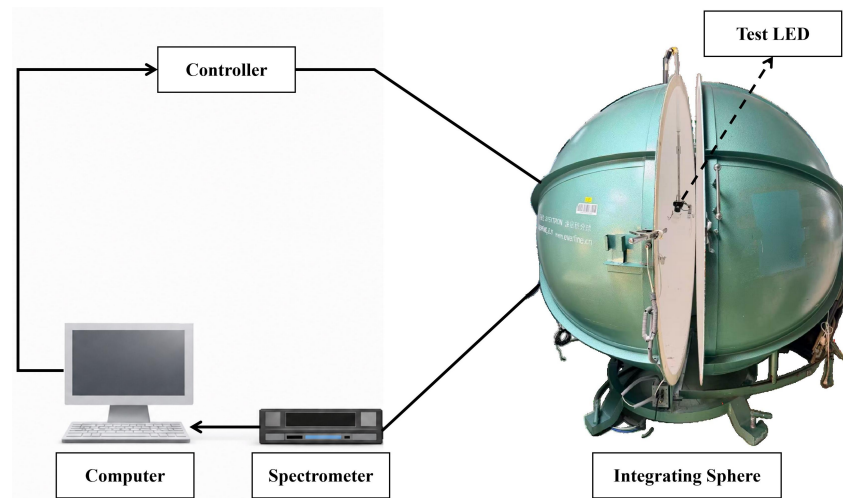


FIGURE 8. Experimental test setup.

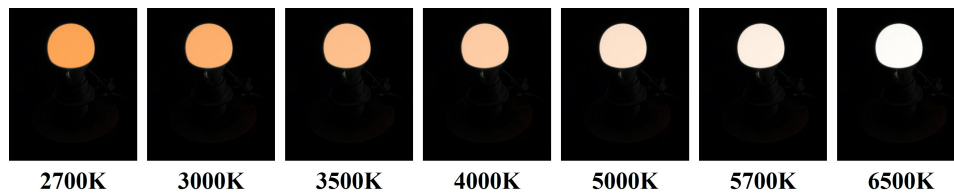


FIGURE 9. Captured images of the seven color temperature levels at maximum brightness.

On this basis, the standard deviation of color matching (SDCM) is used to characterize the proximity between the test color point and reference color point, and its calculation formula is given as follows [19]:

$$(u' - u'_c)^2 + (v' - v'_c)^2 = (0.001n)^2 \quad (38)$$

where (u', v') denotes the chromaticity coordinates of the test color point, (u'_c, v'_c) the chromaticity coordinates of the reference color point, and n the SDCM order. A smaller value of n indicates a smaller chromaticity distance between the test and reference color points. Chromaticity tolerance mainly reflects the proximity between the test and target color points. To further characterize the deviation direction and magnitude of white-light color points relative to the Planckian locus, $D_{u'v'}$ was introduced in this study as a supplementary evaluation metric. The signed distance from the test color point (u', v') to the nearest point (u'_p, v'_p) on the Planckian locus is defined as $D_{u'v'}$, and its calculation formula is expressed as follows [20]:

$$D_{u'v'} = \pm \sqrt{(u' - u'_p)^2 + (v' - v'_p)^2} \quad (39)$$

where the sign of $D_{u'v'}$ indicates the direction of deviation. $D_{u'v'} > 0$ indicates that the measured color point is located above the Planckian locus, whereas $D_{u'v'} < 0$ indicates that the measured color point is located below the Planckian locus. When $D_{u'v'} = 0$, the measured color point is located on the Planckian locus.

Based on the above algorithmic framework and experimental conditions, experiments were conducted at seven correlated

color temperature levels: 2700 K, 3000 K, 3500 K, 4000 K, 5000 K, 5700 K, and 6500 K. Fig. 9 shows the captured images of the seven color temperature levels at the maximum brightness, whereas Fig. 10 presents the chromaticity tolerance results at different brightness levels under different color temperatures. Specifically, Fig. 10(a) and Fig. 10(b) show the chromaticity tolerance results within the 1%–10% and 10%–100% dimming ranges, respectively. It can be observed that the chromaticity tolerance of all color temperature levels can be controlled within a 4-step SDCM over the full dimming range.

Table 5 presents the minimum, maximum, and average values of $D_{u'v'}$ within the 1%–100% dimming range under different target color temperatures. In terms of the extreme values, the minimum values of $D_{u'v'}$ are distributed between -0.0044 and -0.0020 , while the maximum values are distributed between 0.0023 and 0.0046 . This indicates that the white-light

TABLE 5. $D_{u'v'}$ values under different color temperatures within the 1%–100% dimming range.

CCT	Min $D_{u'v'}$	Max $D_{u'v'}$	Avg $D_{u'v'}$
2700K	-0.0020	0.0031	6.68×10^{-4}
3000K	-0.0030	0.0039	2.84×10^{-4}
3500K	-0.0036	0.0040	6.32×10^{-5}
4000K	-0.0040	0.0032	-5.74×10^{-4}
5000K	-0.0035	0.0041	1.46×10^{-3}
5700K	-0.0044	0.0023	-1.29×10^{-3}
6500K	-0.0036	0.0046	-3.68×10^{-5}

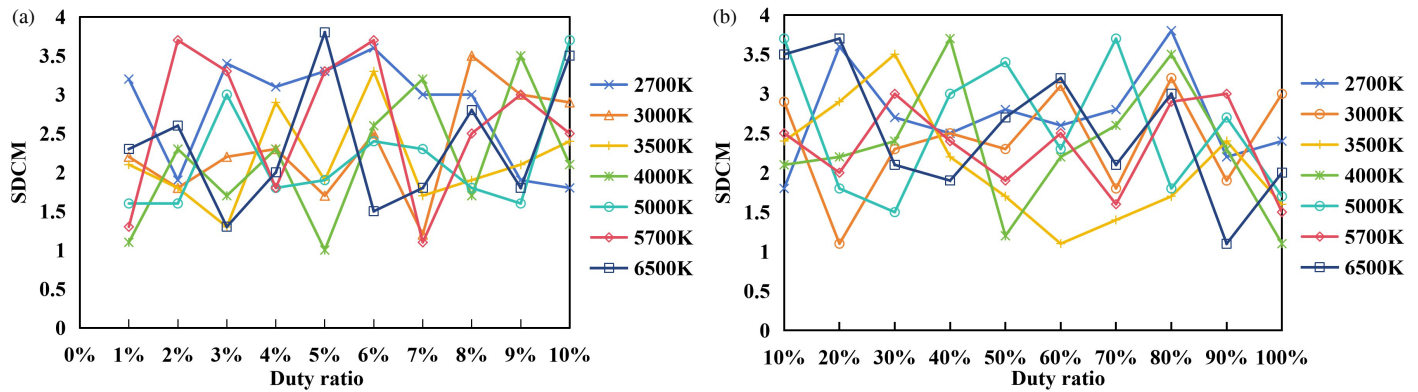


FIGURE 10. Chromaticity tolerance results of different color temperatures at different brightness levels. (a) 1%–10%; (b) 10%–100%.

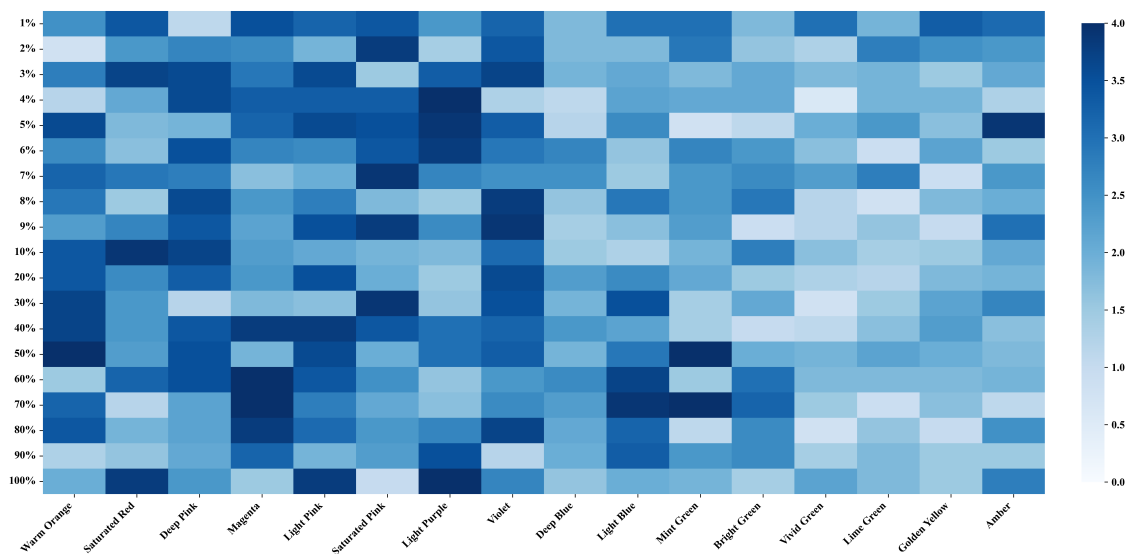


FIGURE 11. Heatmap of chromaticity tolerance results for the 16 colored-light points at different brightness levels.

color points under different color temperatures exhibit a certain degree of positive and negative deviation, but the overall deviation magnitude is relatively small. In general, $D_{u'v'}$ fluctuates within a limited range under each color temperature, suggesting that the deviation of the output white light from the Planckian locus remains relatively small throughout the dimming process, and that the composite chromaticity is maintained with good stability.

Similarly, experiments were conducted on 16 colored-light points. As shown in Fig. 11, the heatmap illustrates the chromaticity tolerance distribution of the 16 colored-light points at different brightness levels. The horizontal axis represents the color category, while the vertical axis represents the brightness level. A darker color indicates a larger chromaticity tolerance. It can be observed that the chromaticity tolerance of all 16 colored-light points can be controlled within a 4-step SDCM over the full dimming range.

To verify the applicability of the proposed algorithm under different operating temperatures, four representative color points, namely 2700 K, Saturated Red, Mint Green, and Deep Blue, were selected. The SDCM variations of these color points

were tested at duty cycles of 5%, 50%, and 100% over the temperature range of 25–60 °C, and the results are shown in Fig. 12. It can be observed that, under different temperature and duty-cycle conditions, the SDCM values of all color points were generally maintained within 4, and no obvious uncontrolled increase was observed. These results indicate that the proposed algorithm remains effective under different ambient temperature conditions and exhibits certain temperature adaptability and practical application stability.

3.3. CAM16 and CAM16-UCS Evaluation and Analysis

As brightness decreases, the human visual system gradually transitions from photopic to mesopic or even scotopic vision. Both the level of visual adaptation and the response weights of different color channels change accordingly. Therefore, even when the geometric position of the test light in the CIE x, y chromaticity diagram changes only slightly, perceptible color differences may still be observed by the human eye [21, 22]. To further evaluate the visual consistency of RGB LED color-mixing results under low-brightness conditions, the CAM16 color appearance model and CAM16-UCS uniform color space

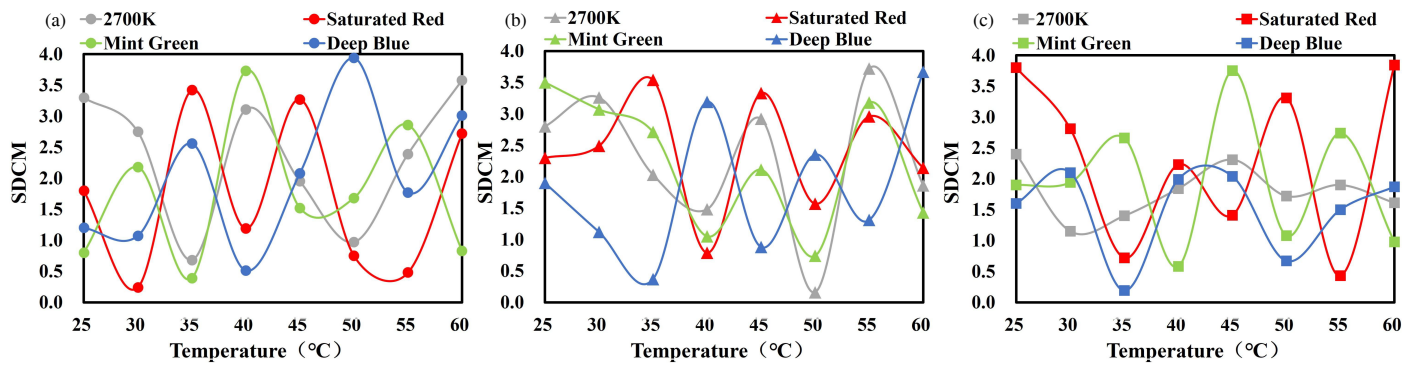


FIGURE 12. SDCM variation with temperature for different color points at 5%, 50%, and 100% brightness levels: (a) 5%, (b) 50%, and (c) 100%.

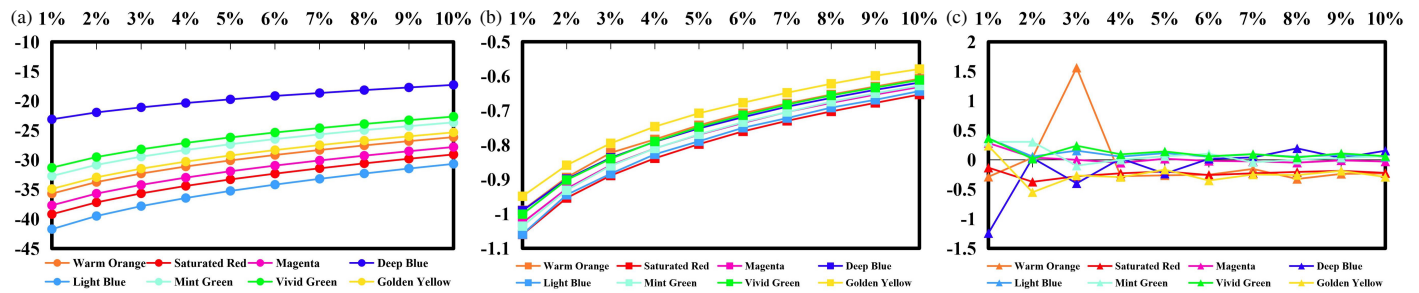


FIGURE 13. CAM16 attribute difference curves of different colored-light points under low-brightness conditions. (a) ΔJ , (b) ΔC , and (c) Δh .

were introduced in this study to analyze the color appearance variations of the calibrated colored light at different brightness levels.

CAM16 can be used to characterize changes in appearance attributes such as lightness, colorfulness C , and hue angle h of colored light. In this study, the differences between the test values at different brightness levels and the values at the 100% reference brightness are defined as follows [23]:

$$\begin{cases} \Delta J = J_{\text{test}} - J_{\text{ref}} \\ \Delta C = C_{\text{test}} - C_{\text{ref}} \\ \Delta h = h_{\text{test}} - h_{\text{ref}} \end{cases} \quad (40)$$

where J_{test} , C_{test} , and h_{test} denote the lightness, colorfulness, and hue angle at the tested brightness level, respectively, and J_{ref} , C_{ref} , and h_{ref} denote the corresponding parameters at the 100% reference brightness level.

On this basis, the CAM16-UCS uniform color space is further used to calculate the color-appearance difference [24]:

$$\Delta E_{\text{CAM16-UCS}} = \sqrt{(J'_{\text{test}} - J'_{\text{ref}})^2 + (a'_{\text{test}} - a'_{\text{ref}})^2 + (b'_{\text{test}} - b'_{\text{ref}})^2} \quad (41)$$

In this equation, J' , a' , and b' denote the lightness dimension and the two chromatic dimensions in the CAM16-UCS space, respectively. To ensure comparability of the results, the spectral data measured at different brightness levels were converted into the CAM16 and CAM16-UCS spaces under unified viewing conditions. The relevant parameter settings are presented in Table 6.

To verify the applicability of this proposed algorithm in different hue regions, eight representative color points were

TABLE 6. Parameter settings for CAM16 and CAM16-UCS.

Parameter	Value	Parameter	Value
Reference White Point	D65	K_L	1.0
L_A	20	c_2	0.007
Y_b	20	c_1	0.0228
Surround	dim	Δh range	$[-180^\circ, 180^\circ]$

selected from the 16 colored-light target points for analysis, namely Warm Orange, Saturated Red, Magenta, Deep Blue, Light Blue, Mint Green, Vivid Green, and Golden Yellow. The selected color points covered the main hue regions, including red, orange, yellow, green, blue, and purple, and included both high-saturation and low-saturation color points. Therefore, the calibration performance of the proposed algorithm for different colored-light points can be better reflected. The spectral data measured by the integrating sphere at low brightness levels were input into the CAM16 color appearance model and compared with the color appearance parameters at a 100% reference brightness level. The line plots of the color appearance parameter deviations at different brightness levels are shown in Fig. 13.

As can be seen from Fig. 13, ΔJ under different brightness conditions exhibits an obvious negative deviation, indicating that the lightness of the test light decreases relative to that at the 100% reference brightness as the brightness is reduced. This result is consistent with the visual variation characteristics during low-brightness dimming. In contrast, the variations in ΔC and Δh are generally small, and most data are close to zero, indicating that the calibrated output colors can maintain good stability in terms of colorfulness and hue.

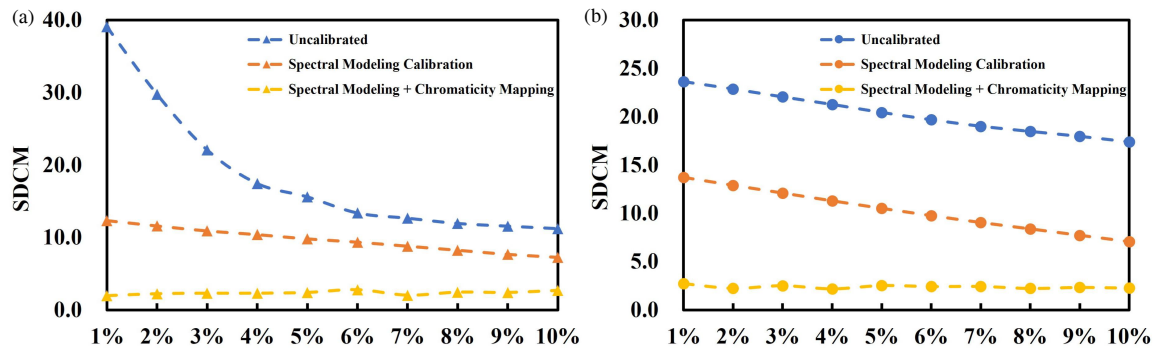


FIGURE 14. Chromaticity tolerance results of different calibration modules. (a) White light and (b) colored light.

To weaken the influence of brightness differences on the evaluation of composite color difference, the measured spectra were normalized before $\Delta E_{CAM16-UCS}$ was calculated. As can be seen from Table 7, within the brightness range of 4%–10%, the average $\Delta E_{CAM16-UCS}$ remains at a relatively low level of 0.0334–0.0810. This indicates that, after the influence of lightness difference is excluded, the color appearance under low-brightness conditions is highly consistent with that at the 100% reference brightness. When the brightness is further reduced to 1%–3%, $\Delta E_{CAM16-UCS}$ increases to some extent, indicating that the stability of LED spectral output decreases under extremely low brightness conditions and that the color appearance difference increases accordingly. Overall, the normalized chroma and hue deviations are maintained within a relatively small range, which verifies the effectiveness of the proposed method.

TABLE 7. Statistical results of $\Delta E_{CAM16-UCS}$ under low-brightness conditions.

Duty	Min	Max	Avg
10%	0.00954593	0.07719547	0.03340616
9%	0.01136946	0.05813511	0.03556557
8%	0.00954593	0.11493647	0.04460407
7%	0.01304980	0.07840958	0.04640862
6%	0.00954593	0.09164864	0.04931206
5%	0.01751436	0.30897609	0.08103470
4%	0.00954593	0.09164864	0.04011681
3%	0.05226090	1.69011500	0.33456236
2%	0.00954593	0.28198972	0.15273650
1%	0.14240027	1.31105335	0.41603744

3.4. Ablation Study Based on Chromaticity Tolerance

To verify the contribution of each module in the proposed calibration method to color consistency at low brightness, an ablation experiment was conducted within the low-brightness range of 1%–10%. Three comparative schemes were set in the experiment: no chromaticity-coordinate calibration, calibration using only the spectral reconstruction module, and the complete cal-

ibration method combining spectral reconstruction with color-point mapping. The results are shown in Fig. 14. Specifically, Fig. 14(a) shows the average chromaticity tolerance results of the seven white-light color points, and Fig. 14(b) shows the average chromaticity tolerance results of the 16 colored-light points.

As shown in Fig. 14, under the uncalibrated condition, the chromaticity tolerance increases significantly in the low-brightness region, indicating that a decrease in duty cycle can lead to changes in the LED spectral distribution and shifts in the mixed chromaticity coordinates. After spectral prediction-based calibration is introduced, the chromaticity tolerance is reduced overall, demonstrating that the influence of primary-color drift on color-mixing results can be effectively mitigated by reconstructing the RGB-channel spectra at different duty cycles and correcting the chromaticity coordinates of individual channels. On this basis, after chromaticity-point mapping is further incorporated, the chromaticity tolerances of both white and colored lights are further reduced with smaller fluctuations, indicating that chromaticity-point mapping can compensate for the target chromaticity deviation caused by changes in the RGB color-gamut triangle under low-brightness conditions, thereby further improving color consistency.

To further quantitatively evaluate the improvement achieved by different calibration modules, Table 8 summarizes the SDCM results of 16 chromaticity points in the 1%–10% low-duty-cycle range, with a total of 160 samples. The

TABLE 8. Statistical comparison of SDCM values under low-brightness dimming conditions.

Method	Mean SDCM	Max SDCM	Min SDCM	Std. SDCM	Reduction of Mean SDCM
Uncalibrated	20.28	24.90	16.00	2.19	—
Spectral Modeling Calibration	10.26	14.80	6.10	2.22	49.42%
Spectral Modeling + Chromaticity Mapping	2.40	4.00	0.60	0.86	88.18%

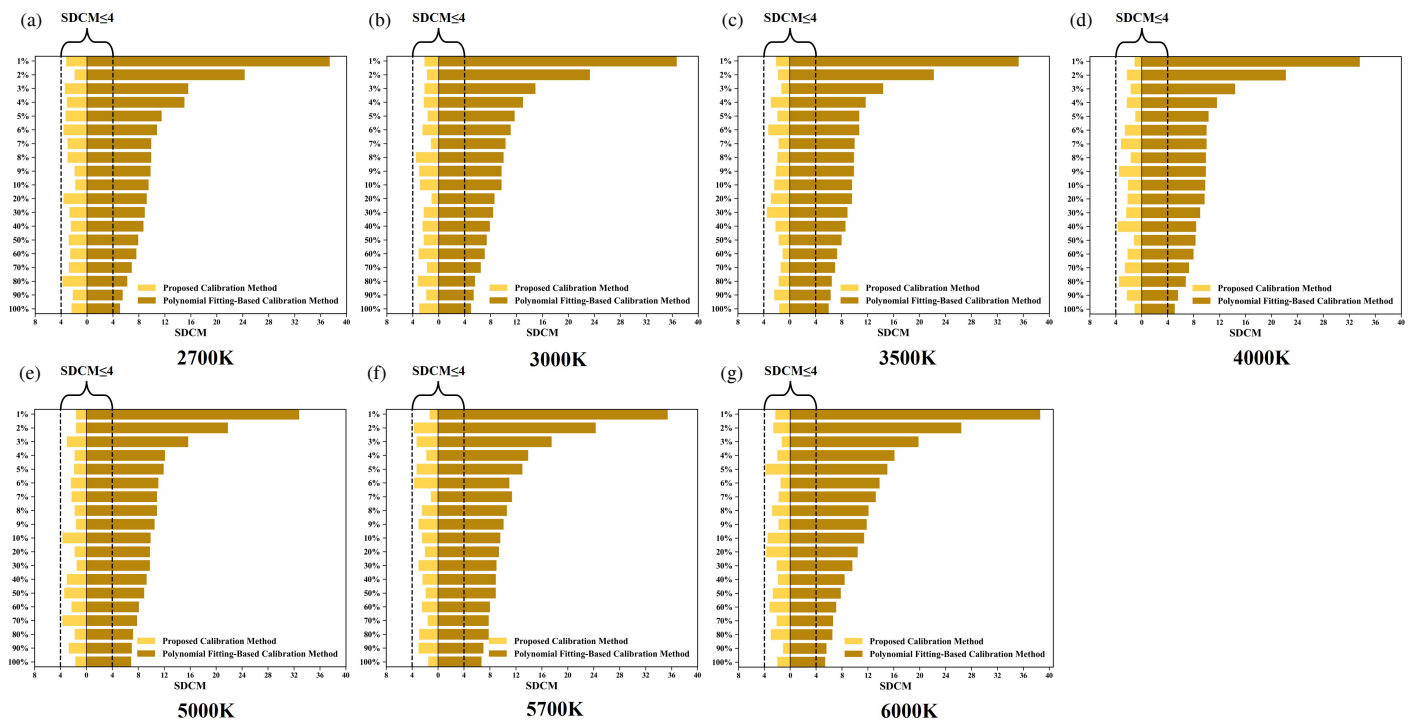


FIGURE 15. Chromaticity tolerance comparison of two calibration algorithms for white-light color mixing at different brightness levels.

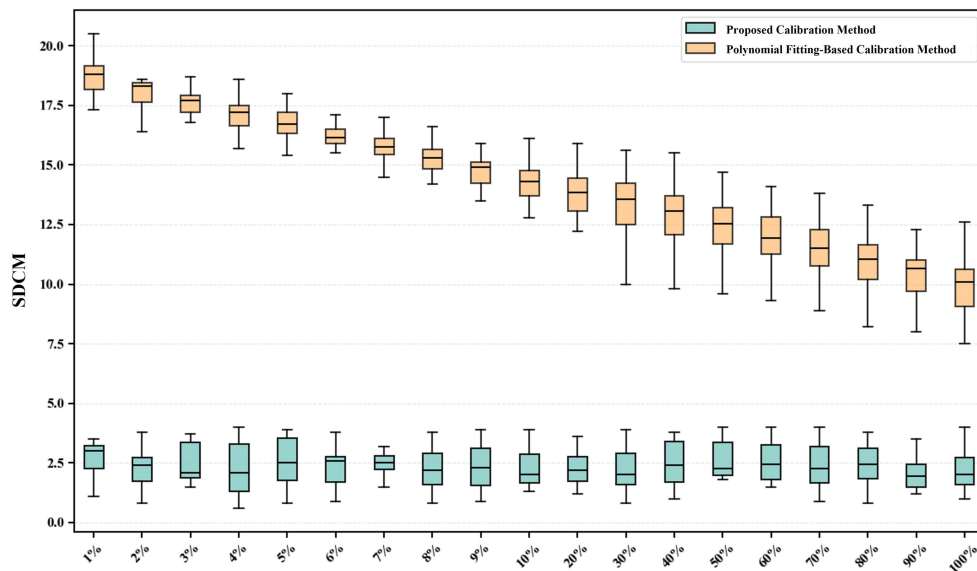


FIGURE 16. Chromaticity tolerance comparison of two calibration algorithms for colored-light color mixing at different brightness levels.

mean, maximum, minimum, and standard deviation values are reported for each method. The results show that when only spectral modeling-based calibration is applied, the mean SDCM decreases from 20.28 to 10.26, corresponding to a reduction of 49.42%. After chromaticity-point mapping is combined, the mean SDCM is further reduced to 2.40, with a reduction of 88.18%. Meanwhile, the maximum SDCM and standard deviation are reduced to 4.00 and 0.86, respectively, indicating that the proposed method can more effectively reduce color deviation and improve color stability under low-brightness conditions.

3.5. Performance Comparison of Different Calibration Methods

Figures 15 and 16 present the chromaticity tolerance comparison results of the white-light color-temperature points and colored-light points, respectively, under the two calibration methods. For the seven target color temperatures, the chromaticity tolerance of the traditional polynomial fitting method can reach up to 38.6 steps. After the spectral modeling and color-point mapping joint calibration method proposed in this study was adopted, the chromaticity tolerance within the 1%–

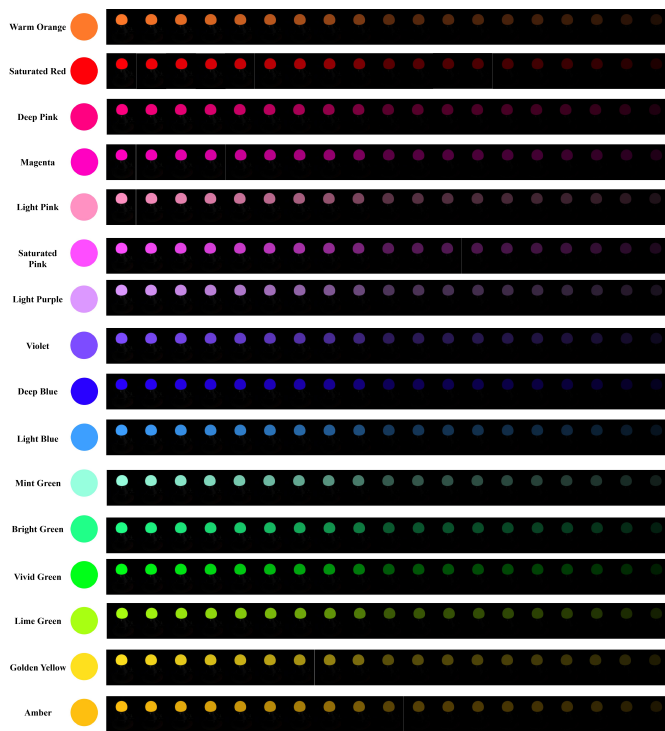


FIGURE 17. Physical images of RGB LED colored-light mixing at different brightness levels.

10% low-brightness range was reduced to approximately 1.0–3.8 steps.

For the 16 colored-light target points, the chromaticity tolerance of the traditional method can reach up to 20.5 steps, and the overall chromaticity tolerance within the low-brightness range is distributed approximately between 11.3 and 20.5 steps. After the proposed method was adopted, the chromaticity tolerance was compressed to approximately 0.6–4.0 steps. The results indicate that the proposed method can significantly reduce the composite color-point deviation caused by spectral variation and primary color drift under low-brightness conditions, thereby improving the color consistency and stability of both white and colored lights during dimming. The physical images of the mixed colored light at different brightness levels are shown in Fig. 17.

4. DISCUSSIONS

The experimental results show that the combination of spectral reconstruction and chromaticity-point mapping is critical for improving color consistency between high- and low-brightness conditions. Spectral reconstruction is used to correct the chromaticity-coordinate drift of individual RGB channels at different duty cycles, while two-dimensional affine mapping compensates for the chromaticity deviation caused by changes in the RGB color-gamut triangle under low-brightness conditions. By combining these two processes, both primary-color drift and color-mixing geometric variation can be considered, allowing the nonlinear effects of low-brightness dimming on color-mixing results to be more accurately described. The ex-

perimental results demonstrate that the proposed method can effectively reduce chromaticity tolerance and color appearance differences, thereby improving visual consistency.

In terms of real-time deployment, the main computational burden of the proposed method is concentrated in the spectral calibration stage. During actual operation, only parameter prediction, chromaticity-coordinate correction, two-dimensional affine mapping, and PWM calculation are required. Therefore, the computational cost is relatively low, making the method suitable for implementation on embedded controllers. The proposed method does not require multi-sensor feedback; however, recalibration is still necessary for LED luminaires of different models, different batches, or after long-term aging. Future work may further incorporate dynamic temperature variation and device aging compensation to improve the method's practical applicability.

5. CONCLUSIONS

In this study, a color-mixing optimization method for high-to-low brightness color consistency in RGB LEDs was proposed to address the degradation of color consistency in intelligent lighting systems during brightness transitions. It was demonstrated that, through spectral parameterization modeling and prediction combined with two-dimensional affine chromaticity-point mapping, the effects of RGB primary-color chromaticity-coordinate drift and changes in the color-mixing geometric relationship under low-brightness conditions can be effectively compensated. The experimental results verified the effectiveness of the proposed method in reducing chromaticity tolerance and decreasing color appearance differences in the low-brightness range. In addition, compared with conventional color-mixing methods, the proposed method exhibited better color stability and visual consistency.

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