

Color Space Mapping and Correction Study Based on Nonlinear Mapping Function and Differential Evolutionary Algorithm

Yinhao Li *, Bin Li, Haoyu Sun

School of Electronic and Information Engineering, Liaoning Technical University, Huludao, China

* Corresponding author: Yinhao Li (Email: 742580206@qq.com)

Abstract: This paper proposes a color mapping and calibration model based on nonlinear mapping functions and optimization algorithms, focusing on the implementation methods for different gamut conversions and LED color calibration. First, a nonlinear mapping function with 21 parameters is constructed. Combined with the total loss function consisting of color difference, gamut constraints, and smoothness loss, the differential evolutionary algorithm is employed to map the BT.2020 gamut to the gamut of ordinary displays, effectively reducing color loss. Secondly, a nonlinear mapping function with 45 parameters is designed, and the differential evolutionary algorithm is also used to optimize the total loss function, realizing the mapping from four-channel to five-channel color spaces while taking both color accuracy and constraint conditions into account. Finally, the coefficient matrix calibration principle and quadratic polynomial mapping scheme are adopted, and the color calibration of LED displays is completed by minimizing the total loss function. This model can achieve accurate conversion of different gamut and color calibration of display devices, with the advantages of efficient parameter optimization, small color loss, and smooth mapping.

Keywords: Nonlinear Mapping Functions; Differential Evolutionary Algorithm; Color Correction.

1. Introduction

This paper focuses on the key technologies of color space mapping and display calibration, aiming to solve the problems of different gamut conversion and device color consistency through nonlinear mapping functions and optimization algorithms [1]. First, in view of the difference between the BT.2020 gamut and the gamut of ordinary displays, a nonlinear mapping function with 21 parameters is constructed. Combined with the total loss function composed of color difference, gamut constraints and smoothness loss, the differential evolutionary algorithm is used to achieve accurate color mapping and reduce conversion loss [2] [3]. Secondly, to meet the requirement of high-dimensional mapping from four-channel to five-channel color space, a nonlinear mapping function with 45 parameters is designed. The same optimization framework is used to balance color fidelity and physical constraints, ensuring the visual consistency of conversion [4] [5]. Finally, regarding the pixel differences of LED displays, based on the coefficient matrix calibration principle and quadratic polynomial mapping, a loss function is constructed to optimize parameters, thereby improving the color uniformity of the entire screen [6] [7]. Experimental results show that the proposed method maintains high color accuracy in different gamut conversions and effectively improves the color consistency of LED displays, verifying the effectiveness and practicability of the model.

2. BT.2020 to display gamut mapping model based on nonlinear mapping and differential evolutionary algorithm

In modern display technology, accurate color reproduction is a key issue. The difference between the BT.2020 gamut and

the gamut of ordinary displays leads to a problem: how to accurately map colors in the BT.2020 gamut to the gamut of ordinary displays while minimizing color loss. This paper introduces a method based on nonlinear mapping functions and optimization algorithms to solve this problem.

These two gamuts present different triangular regions on the CIE 1931 chromaticity diagram. The goal is to design a mapping function to map colors in the BT.2020 gamut to the display gamut while minimizing color loss.

2.1. Construction of the mapping function

To achieve this goal, a nonlinear mapping function is designed. This function consists of 21 parameters, with 7 parameters for each channel (R, G, B), including 3 linear terms, 3 quadratic terms, and 1 constant term. Specifically, for an input RGB color, the mapped color can be calculated using the following equations:

$$R_{mapped} = a_1R + a_2G + a_3B + a_4R^2 + a_5G^2 + a_6B^2 + a_7 \quad (1)$$

$$G_{mapped} = a_8R + a_9G + a_{10}B + a_{11}R^2 + a_{12}G^2 + a_{13}B^2 + a_{14} \quad (2)$$

$$B_{mapped} = a_{15}R + a_{16}G + a_{17}B + a_{18}R^2 + a_{19}G^2 + a_{20}B^2 + a_{21} \quad (3)$$

Where, a_1, a_9, a_{17} represent the linear self-mapping coefficients of the R, G, and B channels respectively, which are used to adjust the intensity of each channel. $a_2, a_3, a_8, a_{10}, a_{15}, a_{16}$ represent the cross-influence coefficients between channels, which are used to adjust the interaction between different channels. $a_4, a_5, a_6, a_{11}, a_{12}, a_{13}, a_{18}, a_{19}, a_{20}$ represent the quadratic term coefficients, which are used to enhance the nonlinear mapping capability and handle complex gamut conversions. a_7, a_{14}, a_{21} represent the constant terms, which are used to adjust the offset of each channel.

2.2. Construction of the loss function

To optimize these parameters, a total loss function is defined, which consists of three components: color difference loss, gamut constraint loss, and smoothness loss. The color difference loss is measured by calculating the difference between colors before and after mapping in the CIE Lab space. The formula for the color difference loss is:

$$L_{color} = \sum_{i=1}^N \|\Delta E_{Lab}(y_i, t_i)\|_2^2 \quad (4)$$

Among them, Lab_1 and Lab_2 are the Lab representations of the source color and the mapped color, respectively.

The gamut constraint loss ensures that the mapped color is within the display gamut. If the mapped color exceeds the display gamut, a gamut loss is introduced. The formula for the gamut constraint loss is:

$$L_{gamut} = \sum_{i=1}^N (\max(0, y_i - 1)^2 + \max(0, -y_i)^2) \quad (5)$$

Among them, y_i represents the mapped color in the display gamut. The smoothness loss ensures the smoothness of the mapping function through L2 regularization of parameters. The formula for the smoothness loss is:

$$L_{smooth} = \sum_{i=1}^M \|w_i\|_2^2 \quad (6)$$

Among them, w_i represents the parameters of the mapping function. The total loss function can be expressed as:

$$L_{total} = \lambda_{color} \cdot L_{color} + \lambda_{gamut} \cdot L_{gamut} + \lambda_{smooth} \cdot L_{smooth} \quad (7)$$

Among them, $\lambda_{color} = 1.0$, $\lambda_{gamut} = 2.0$, and $\lambda_{smooth} = 0.1$ are the weights of the loss function, used to balance the importance of different loss terms.

2.3. Model solution based on the differential evolutionary algorithm

To minimize the total loss function, differential evolutionary optimization algorithm. The core idea of the differential evolutionary algorithm is to generate new solutions by perturbing the difference vectors among the individuals of the population, and then keep the high-quality solutions by competitive selection, so as to gradually approach the global optimum. The algorithm adopts a population size of 200 individuals, and each individual represents a complete set of parameters. The specific steps are as follows:

First, the population is initialized by setting the main diagonal linear term coefficients to $[0.7, 1.3]$, the non-diagonal linear term coefficients to $[-0.3, 0.3]$, the quadratic term coefficients to $[-0.1, 0.1]$, and the constant term to $[-0.05, 0.05]$, respectively. The variance factor F was then adaptively adjusted in the range $[0.4, 0.9]$ using the DE/best/1 strategy:

$$v_i = x_{best} + F(x_b - x_c) \quad (8)$$

Where x_{best} is the optimal individual in the current population, and x_b and x_c are two different individuals chosen at random.

After that, binomial crossover was used with crossover probability $CR = 0.9$.

$$u_{i,j} = \begin{cases} v_{i,j} & \text{if } rand_j \leq CR \text{ or } j = j_{rand} \\ x_{i,j} & \text{otherwise} \end{cases} \quad (9)$$

Where j_{rand} is a randomly chosen position of a parameter, ensuring that at least one parameter crosses over. One-to-one greedy selection is used:

$$x_i^{new} = \begin{cases} u_i & \text{if } f(u_i) < f(x_i) \\ x_i & \text{otherwise} \end{cases} \quad (10)$$

The iteration is terminated when the maximum number of

iterations is reached or when the improvement of the optimal solution is less than a threshold.

From the optimization loss history graph in Figure 1, it can be observed that the loss value drops sharply in the first few iterations, which reflects the rapid progress of the model in the initial learning stage. As the number of iterations increases, the rate of decrease in the loss value gradually slows down until it approaches zero, indicating that the model has approached or reached the optimal solution.

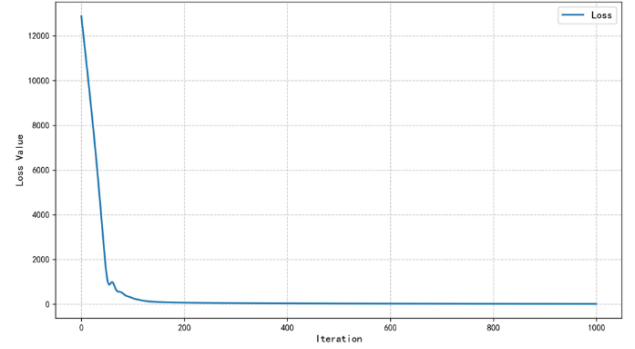


Figure 1. Loss optimization curve

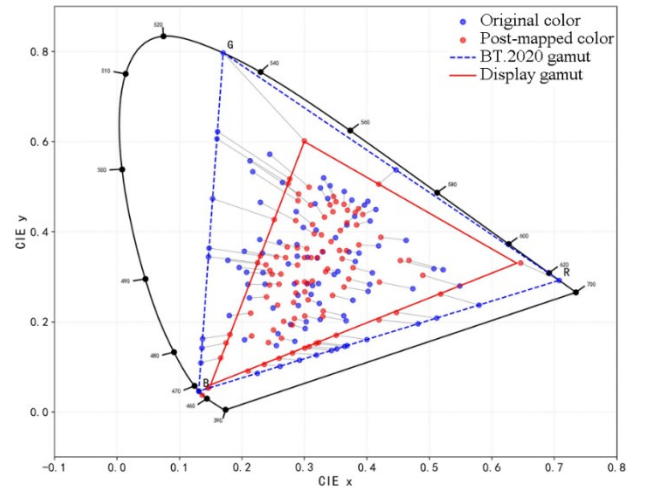


Figure 2. Color space conversion mapping effect

As shown in Figure 2, to verify the mapping effect, a series of test color samples were generated and mapped to the display gamut. Then, the mapping results were visualized on the CIE 1931 chromaticity diagram. The results indicate that this method can effectively map colors in the BT.2020 gamut to the display gamut while maintaining high color accuracy.

3. Four-channel to five-channel color space mapping model based on nonlinear mapping and differential evolutionary algorithm

In modern display technology, it is often necessary to map a four-channel color space (RGBV) to a five-channel color space (RGBCX). This process not only needs to maintain the visual consistency of colors but also meet gamut constraints and weight constraints. Essentially, this is a high-dimensional nonlinear optimization problem that requires balancing color fidelity and physical constraints.

3.1. Construction of the mapping function

To realize the color space mapping from four-channel

(RGBV) to five-channel (RGBCX), a nonlinear mapping function is designed in the research. This function contains 45 parameters, with 9 parameters for each output channel (R, G, B, C, X), including 4 linear terms, 4 quadratic terms, and 1 constant term. Specifically, for the input RGBV color, the mapping calculation formulas for the five channels (R, G, B, C, X) are as follows:

$$R_{mapped} = a_1R + a_2G + a_3B + a_4V + a_5R^2 + a_6G^2 + a_7B^2 + a_8V^2 + a_9 \quad (11)$$

$$G_{mapped} = a_{10}R + a_{11}G + a_{12}B + a_{13}V + a_{14}R^2 + a_{15}G^2 + a_{16}B^2 + a_{17}V^2 + a_{18} \quad (12)$$

$$B_{mapped} = a_{19}R + a_{20}G + a_{21}B + a_{22}V + a_{23}R^2 + a_{24}G^2 + a_{25}B^2 + a_{26}V^2 + a_{27} \quad (13)$$

$$C_{mapped} = a_{28}R + a_{29}G + a_{30}B + a_{31}V + a_{32}R^2 + a_{33}G^2 + a_{34}B^2 + a_{35}V^2 + a_{36} \quad (14)$$

$$X_{mapped} = a_{37}R + a_{38}G + a_{39}B + a_{40}V + a_{41}R^2 + a_{42}G^2 + a_{43}B^2 + a_{44}V^2 + a_{45} \quad (15)$$

Among them, the linear term parameters are the linear mapping coefficients from the source gamut channels (R, G, B, V) to the target gamut channels (R, G, B, C, X), which are used to adjust the intensity of each channel. The quadratic term coefficients are employed to enhance the nonlinear mapping capability and handle complex gamut conversions. The parameter at the end of the formula is the constant term, which serves to adjust the offset of each channel.

3.2. Construction of the loss function

To optimize these parameters, a total loss function is defined, which consists of three components: color difference loss, gamut constraint loss, and smoothness loss. For the calculation of color difference loss, the source color (RGBV) and the mapped color (RGBCX) are first converted to the XYZ space. Subsequently, the colors in the XYZ space are converted to the Lab space. The color difference is then measured by calculating the Euclidean distance between the source color and the mapped color in the Lab space.

$$L_{distance} = \sum_{i=1}^N \|y_i - t_i\|_2^2 \quad (16)$$

$$L_{color} = \sum_{i=1}^N \|\Delta E_{Lab}(y_i, t_i)\|_2^2 \quad (17)$$

The gamut constraint loss ensures that the mapped colors lie within the display gamut.

$$L_{gamut} = \sum_{i=1}^N (\max(0, y_i - 1)^2 + \max(0, -y_i)^2) \quad (18)$$

Color tone loss calculates the absolute difference between the display color and the target color, focusing on the fine tuning of the color. It focuses on making the display hue match the target hue as closely as possible by adjusting the color of the model output.

$$L_{tone} = \sum_{i=1}^N |y_i - t_i| \quad (19)$$

The total loss function is:

$$L_{total} = L_{color} + 0.5 * L_{distance} + 0.2 * L_{gamut} + 0.3 * L_{tone} \quad (20)$$

3.3. Model solution based on differential evolutionary algorithm

Optimize the parameters using a differential evolutionary algorithm. Calculate the fitness value of each individual in the current population and record the optimal individual. For each individual, adaptive F-values are used to generate variant individuals, crossover operations are used to generate test

individuals, and fitness values of test individuals are calculated. A selection operation is used to decide whether to update the current individual or not.

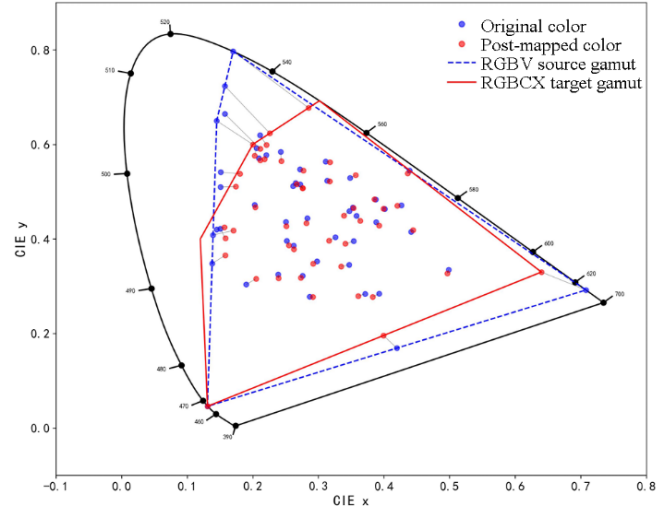


Figure 3. Color space conversion (4-channel to 5-channel) conversion effect diagram

Through the above steps, the parameters of the mapping function are successfully optimized, and high-quality color mapping from the RGBV gamut to the RGBCX gamut is realized. To verify the mapping effect, a series of test color samples are generated and mapped to the RGBCX gamut. The mapping results are visualized on the CIE 1931 chromaticity diagram, as shown in Figure 3. The results demonstrate that this method can effectively map colors in the RGBV gamut to the RGBCX gamut while maintaining high color accuracy.

4. LED display color correction model based on quadratic polynomial mapping and loss optimization

To improve the color consistency of LED displays, it is necessary to develop an accurate correction algorithm to address inconsistencies in pixel display effects caused by various factors.

4.1. Establishment of the correction model

The coefficient matrix correction principle is adopted to achieve color correction for LED displays. This method is based on the core idea that by adjusting the three color components of red, green, and blue (RGB) of the LED, the brightness and chromaticity of each display pixel can be precisely controlled. Specifically, PWM (Pulse Width Modulation) technology is used to adjust the brightness of the LED, while for chromaticity correction, the interaction of the three RGB components needs to be comprehensively considered.

To implement color correction, a scheme based on quadratic polynomial mapping is adopted. The same form of mapping function is used to handle crosstalk between channels and nonlinear response issues. The goal here is to correct the RGB input signals of each pixel to compensate for color deviations caused by manufacturing differences and aging, thereby improving the color uniformity and accuracy of the display. Quadratic terms are used to model nonlinear responses, and linear terms handle cross-influences between channels. By optimizing parameters, full-screen color consistency is achieved.

4.2. Loss function and parameter solution based on optimization algorithm

By minimizing the loss value, the corrected results can be made closer to the ideal state. The loss function consists of four parts: color loss, gamut constraint loss, total variation loss and smoothness loss, which together ensure the accuracy and stability of the correction effect.

The color loss is measured by calculating the Euclidean distance between the pre-correction and post-correction colors in the CIE Lab space to ensure that the corrected color is as close as possible to the target color.

$$L_{color} = \sum_{i=1}^N \|\Delta E_{Lab}(y_i, t_i)\|_2^2 \quad (21)$$

Total variation loss is a smoothing loss used in image processing to reduce unnatural edges or noise in an image.

$$L_{tv} = \sum_{i=1}^N (\|y_i^h\|_1 + \|y_i^v\|_1) \quad (22)$$

Where y_i^h and y_i^v are the horizontal and vertical differentials, respectively.

The gamut constraint loss ensures that the corrected color values are within the gamut range of the display to avoid color distortion caused by exceeding the display range.

$$L_{gamut} = \sum_{i=1}^N (\max(0, y_i - 1)^2 + \max(0, -y_i)^2) \quad (23)$$

The smoothness loss is achieved through L2 regularization of the parameters, aiming to maintain the smoothness of the mapping function, avoid overfitting, and thus improve the generalization ability of the correction results.

$$L_{smooth} = \sum_{i=1}^M \|w_i\|_2^2 \quad (24)$$

Therefore, the total loss function is:

$$L_{total} = L_{color} + 0.5 * L_{tv} + 0.2 * L_{gamut} + 0.05 * L_{smooth} \quad (25)$$

By minimizing the total loss function, it can be ensured that the corrected color not only accurately reflects the target color but also maintains good uniformity and stability within the gamut range, thereby achieving a correction effect closer to the ideal.

4.3. Evaluation and analysis of correction results

To evaluate the correction effect, color difference metrics and smoothness metrics are calculated. The color difference metric is measured using the Euclidean distance in the Lab space, and the smoothness metric is measured by calculating the gradient magnitude of the corrected data.

To improve computational efficiency, a batch processing method of 16×16 pixel blocks is adopted. Each 16×16 pixel block of the image is traversed, the loss of each block is calculated, and these losses are accumulated to obtain the total loss.

In the early stage of optimization, the significant reduction in the loss value reveals the model's ability to quickly absorb information and conduct effective learning. With the deepening of iterations, the decreasing amplitude of the loss value begins to gradually reduce, which indicates that the model is refining its parameters to achieve more precise color correction. The curve tends to be flat in the later stage, and the loss value drops to 0.423136 at the 1000th iteration. This value is significantly lower than the initial value, showing that the model has achieved remarkable results in reducing color deviation and improving display consistency. The decreasing trend of the loss value and the final low value indicate the effectiveness of the model's correction strategy, and also verify the success of the adopted optimization method. In addition, the optimized average color difference (ΔE) is 7.22, the maximum color difference (ΔE) is 12.66, and the standard deviation of color difference is 1.56. These indicators all show that the optimized color output has high consistency and accuracy.

As shown in Figure 4, the uncorrected LED display exhibits color inhomogeneity in the "Original Response" on the left. This inhomogeneity is mainly caused by factors such as manufacturing differences and aging. The "Target Image" in the middle shows a uniform gray, representing the ideal state that the corrected display is expected to achieve. The "Optimization Result" image on the right presents the outcome after applying the color correction algorithm. Compared with the original response, the optimized result has significantly improved color uniformity and is closer to the uniform gray of the target image, indicating that the correction algorithm has effectively reduced color deviations on the display.

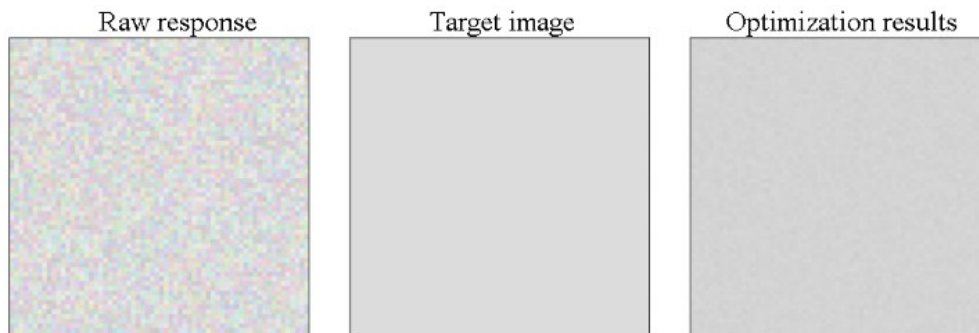


Figure 4. LED display three-channel merge comparison

5. Conclusions

This paper proposes a color processing model based on nonlinear mapping functions and the differential evolutionary algorithm, which demonstrates significant advantages in different gamut conversions and display calibrations, and can

effectively improve the accuracy of color mapping and the consistency of device display. First, for the conversion from BT.2020 to the gamut of ordinary displays, the constructed 21-parameter nonlinear mapping function combined with multi-loss term optimization can maximize the retention of original color information while constraining the gamut range,

solving the problem of color loss in cross-gamut mapping. Secondly, for high-dimensional color conversion from four-channel to five-channel, the 45-parameter mapping function, through refined design of linear and quadratic term parameters, balances visual consistency and physical constraints in complex color space conversion, achieving accurate mapping in high dimensions. Then, for LED display calibration, the mapping scheme based on coefficient matrix and quadratic polynomial effectively compensates for pixel differences through batch optimization, significantly improving the color uniformity of the entire screen and solving display deviations caused by device manufacturing and aging. Finally, all three types of models adopt multi-loss term weighted optimization and the differential evolutionary algorithm, ensuring the efficiency of parameter adjustment and the smoothness of mapping functions, and providing a unified and reliable technical framework for color processing in different scenarios. Future research can further explore the mapping efficiency of higher-dimensional color spaces, or combine deep learning to improve the adaptability of the model to complex scenarios.

References

- [1] Feng Jun, Yan Limin, Chen Jing. An optimization algorithm for RGB to RGBW color gamut conversion[J]. Optoelectronics Technology, 2015, 35(02): 135-139+143. DOI:10.19453/j.cnki.1005-488x.2015.02.015.
- [2] Wei Na, Guo Xiaoqiang, Rao Feng. ITU standardization of ultra-high-definition television color gamut and dynamic range conversion method tracking study[J]. Radio and Television Information, 2021, 28(04): 39-44. DOI:10.16045/j.cnki.rti.2021.04.012.
- [3] Zhou Jun, Qiu Yiming, Gu Yujie, et al. Research on optimized water withdrawal strategy of reservoir pumping station based on differential evolutionary algorithm[J]. Water Resources Science and Economy, 2025, 31(05): 85-89.
- [4] Deng Yicheng, Miao Jing, Ding Tiefu, et al. A real-time gamut correction method for color distortion in LED displays [J]. Electronic Science and Technology, 2014, 01(03): 319-321. DOI:10.16453/j.issn.2095-8595.2014.03.013.
- [5] Zhao Xingmei, Research on point-by-point correction technology for non-uniformity of LED display brightness [D]. Xi'an University of Electronic Science and Technology, 2009.
- [6] Zhou Chunli, Lv Xikun, Xie Wenxin, et al. Study on LED light color quality and optimization [J]. Journal of Lighting Engineering, 2024, 35(01): 15-23.
- [7] Ding Baxiu. Research on color gamut transformation technology of LED display based on polynomial regression approximation[D]. Graduate School of Chinese Academy of Sciences (Changchun Institute of Optical Precision Machinery and Physics), 2013.