Research on Textile Dyeing Formulation Based on Young's Double-Slit Interference Experiment Optimization Algorithm

Junyu Tam[1], Yi Chen[1], Junyu Wu[2, *]

[1]Business School, SunYat-sen University, Shenzhen, 518107, China

[2]School of Electronics and Communication Engineering, SunYat-sen University, Shenzhen, 518107, China

* Corresponding Author Email: wujy325@mail2.sysu.edu.cn

Abstract. With the development of intelligent algorithms, computer color matching has become an important method to improve product quality and save labor cost in printing and dyeing industry. In this paper, based on the K-M optical theory and the color difference theory of CIELAB uniform color space, and combined with the latest heuristic optimization algorithm "Young's Double-Slit Interference Experiment Optimizer (YDSE)" proposed in 2023, a feasible solution to generate textile dyeing formulas quickly is proposed. The model is tested with 12 textile target samples, and the experiments show that the proposed dyeing formulation model can converge quickly, and the color parameters of the generated scheme are closer to those of the real samples, with the maximum parameter error not exceeding 10^{-2} orders of magnitude, and the predicted color differences of the optimal scheme are all in the range of 10^{-6} orders of magnitude or less. Simultaneous testing of the sample formulations using three other common optimization algorithms, WOA, HHO, and IHHO, shows that their predicted color differences are greater than those of YDSE, proving the reliability of the model.

Keywords: Textiles, color matching, K-M optical model, CIELAB uniform color space, Young's double-slit interference experiment optimizer.

1. Introduction

With the gradual expansion of the scale of the printing and dyeing industry, the related enterprises need to control the cost under the satisfaction of consumer demand. In this industry, companies mainly rely on computers to find quality color matching solutions [1][2]. The automatic color matching technology of computers reduces the cost of color matching and also ensures the accuracy of color matching to meet the needs of producers. Textiles are the main production raw materials for the apparel and furniture industries, and good color matching can dramatically increase the aesthetics of the product, improve the consumer's willingness to buy, and create market value. Therefore, the research on the optimization of textile color matching scheme has important theoretical significance and practical value. The use of computer algorithms for color matching and color prediction has many successful cases, Jianguo R [3] and other scholars used polynomial regression algorithms to optimize the color matching of camouflage design, resulting in a minimum color difference of 1.691 and a maximum color difference of 2.497. Sun Xianqiang [4] and other scholars used neural network prediction model to predict the full-color mixing of colored fibers, showing that the average color difference was 1.691, the average color difference was 2.497, and the average color difference was 2.497. Gao Jiale[5] and other scholars in 2023 based on chaotic sparrow algorithm to match the color of fur materials, the average value of the color difference is 0.105. More and more excellent algorithms appear, which provides more optional solutions for the dyeing industry. Combing through the literature, it can be found that there are fewer studies using intelligent optimization algorithms to optimize the color matching scheme, and some studies applying optimization algorithms are more likely to use the Stearns-Noechel theory to construct an optimization model [6][7][8].Kubelka-Munk as a classical optical model is widely used in the dyeing industry [9][10][11], the CIELAB uniform color space constructs a more standard color system, which makes the computer's calculation results have a stronger correlation with human eye vision [12], and CIELAB's theory has also been widely used in research in the field of color matching [13]. Considering the above problems, this paper will be based on the Kubelka-Munk (K-M) optical theory and the color difference theory of CIELAB uniform color space, and adopt the new optimization algorithm "Yang's Double Slit Interference Optimizer (YDSE)" proposed in 2023 for the optimization of textile dye formulations to find the value of intelligent optimization algorithms in the field of color matching. algorithm in the field of color matching.

2. K-M optical model

The K-M optical model was proposed by P. Kubelka and F. Munk in 1931 for the analysis of strongly scattering media illuminated by diffuse light. In the field of color matching, the K- M model is often mixed with the color mixing and summation law and evolved into the K-M single constant theory. The relevant theoretical foundations involved in this study are briefly described below.

2.1. The K- M equation and the colorant addition and mixing law

The K-M equation is generally used to describe the relationship between the reflectance R and the absorption coefficient K and scattering coefficient S of a coloring material, and its general expression is as follows:

$$R^{\infty}(\lambda) = 1 + \frac{K(\lambda)}{S(\lambda)} - \sqrt{[\frac{K(\lambda)}{S(\lambda)}]^2 + \frac{2K(\lambda)}{S(\lambda)}} \tag{1}$$

where $R\infty(\lambda)$ is the reflectance of the sample, $K(\lambda)$ and $S(\lambda)$ are the absorption coefficient and scattering coefficient of the material, respectively. According to the law of additive mixing of colorants, the K value and S value of the colorant have a linear relationship with the concentration, for coloring on a substrate with an absorption coefficient of K_0 and a scattering coefficient of S_0, the absorption and scattering coefficients of the mixture at λ can be defined as:

$$K_\lambda = K_\lambda^0 + \sum_{i=1} c_i k_\lambda^i \tag{2}$$

$$S_\lambda = S_\lambda^0 + \sum_{i=1} c_i s_\lambda^i \tag{3}$$

where c_i is the concentration of colorant i, and K^i_λ and S^i_λ are the absorption coefficient K and scattering coefficient S, respectively, assigned to the color mixture per unit concentration of colorant i.

2.2. K- M single constant theory

The K- M single constant theory is mostly used in the study of textile dyeing, which matches the sample material selected in this study, so the K- M single constant theory is applied for modeling. The model can be derived by combining the K- M equation introduced in the previous section with the color addition and mixing law. First, Eq. (2) is divided with Eq. (3) to obtain:

$$\frac{K_\lambda}{S_\lambda} = (\frac{K}{S})_\lambda = \frac{K_\lambda^0 + \sum_{i=1} c_i k_\lambda^i}{S_\lambda^0 + \sum_{i=1} c_i s_\lambda^i} \tag{4}$$

Due to the rougher surface of the textile, the scattering coefficient s of the colorant is negligible with respect to the scattering coefficient S_0 of the substrate. Therefore there is:

$$\sum_{i=1} c_i s_\lambda^i \approx 0 \tag{5}$$

Bringing this into Eq. (4) gives:

$$(\frac{K}{S})_\lambda = (\frac{K}{S})^0_\lambda + \sum_{i=1} c_i (\frac{k}{s})^i_\lambda \tag{6}$$

where $(K/S)_\lambda$ is the ratio of the absorption coefficient K to the scattering coefficient S of the mixture at wavelength λ, referred to as the K/S value; $(K/S)^0_\lambda$ is the ratio of K_0 to S_0 of the substrate at wavelength λ, and $(k/s)^i_\lambda$ is the ratio of k^i_λ to s^i_λ of the colorant i at wavelength λ. At this time equation (1) becomes:

$$R(\lambda) = 1 + (\frac{K}{S})_\lambda - \sqrt{(\frac{K}{S})_\lambda^2 + 2(\frac{K}{S})_\lambda} \tag{7}$$

This equation constructs the relationship between the K/S value and reflectance R of dyed textiles, which reduces the complexity of the modeling and calculation process.

3. Color difference theory of CIELAB uniform color space

The CIELAB uniform color space is an extended version of the CIELAB color space formulated by the International Commission on Illumination (CIE) in 1976. It improves the uniformity of the color space through transformation to make the evaluation of color differences more accurate. The color difference ΔE value will be more accurate here. It is easy to define and calculate, so this study selects the color difference of CIELAB uniform color space as the objective function of textile color matching optimization modeling.

CIELAB uses three parameters defined by luminance (L*), red-greenness (a*), and yellow-blueness (b*). L*, a*, and b* can be calculated by the following equation:

$$\begin{cases} L^* = 116(\frac{Y}{Y_0})^{\frac{1}{3}} - 16 \\ a^* = 500[(\frac{X}{X_0})^{\frac{1}{3}} - (\frac{Y}{Y_0})^{\frac{1}{3}}] \\ b^* = 200[(\frac{Y}{Y_0})^{\frac{1}{3}} - (\frac{Z}{Z_0})^{\frac{1}{3}}] \end{cases} \tag{8}$$

where, X_0, Y_0, Z_0 denote the tri-stimulus values of ideal white, which are 98.43, 100.00, and 107.38, respectively. the tri-stimulus values X, Y, and Z are calculated to satisfy the following equation:

$$\begin{cases} X = k\int_{400}^{700} S(\lambda)\bar{x}(\lambda)R(\lambda)d(\lambda) \\ Y = k\int_{400}^{700} S(\lambda)\bar{y}(\lambda)R(\lambda)d(\lambda) \\ Z = k\int_{400}^{700} S(\lambda)\bar{z}(\lambda)R(\lambda)d(\lambda) \end{cases} \tag{9}$$

where $S(\lambda)$ is the spectral energy distribution, $x(\lambda)$, $y(\lambda)$, $z(\lambda)$ are the tri-stimulus values of the observer's spectrum, $R(\lambda)$ is the spectral reflectance, and k is a constant taken as 0.1. For the case where X/X_0, Y/Y_0, and Z/Z_0 have at least one value less than 0.008856, the values of L*, a*, and b* are computed according to the following equation:

$$\begin{cases} L^* = 903.3(\frac{Y}{Y_0}) \\ a^* = 3893.5(\frac{X}{X_0} - \frac{Y}{Y_0}) \\ b^* = 1557.4(\frac{Y}{Y_0} - \frac{Z}{Z_0}) \end{cases} \tag{10}$$

Under the CIELAB uniform color space, the color difference *ΔE* between two colors can be defined as:

$$\Delta E^{*} = (\Delta L^{*2} + \Delta a^{*2} + \Delta b^{*2})^{\frac{1}{2}} \tag{11}$$

where *ΔL**, *Δa**, and *Δb** are the difference between the two colors *L**, *a**, and *b**.

4. Overview of the YDSE optimization algorithm

Young's Double Slit Interference Experiment Optimizer (YDSE) is a heuristic optimization algorithm based on the classic wave optics experiment - Young's Double Slit Interference Experiment [14]. This algorithm is based on Huygens' principle and finds the optimal solution to the optimization problem by simulating the interference phenomenon of monochromatic light waves passing through two slits. The relevant mechanisms and optimization principles of this algorithm are introduced below.

4.1. Initialization

YDSE first creates a monochromatic light wave of size *NP* and applies Huygens' principle to calculate the points on the new wavefront after passing through the first slit (FS) and the second slit (SS). For an optimization problem containing *j* decision variables, the process can be expressed as follows.

$$S_{i,j} = Lb_j + rand \times (Ub_j - Lb_j) \tag{12}$$

$$FS_i = S_i + L \times rand_1(-1,1) \times (S_{mean} - S_i), i = 1,1,..., NP \tag{13}$$

$$SS_i = S_i + L \times rand_2(-1,1) \times (S_{mean} - S_i), i = 1,1,..., NP \tag{14}$$

$S_{i,j}$ in Eq. (11) denotes the j^{th} component of the i^{th} monochromatic wave, Ub_j and Lb_j denote the upper and lower bounds of the *j*th decision variable, respectively, and *rand* is a random number in the range [0,1]. FS_i and SS_i in Eqs. (12)(13) denote the ith point created on FS and SS, respectively, *L* denotes the distance between the light source and the barrier, S_i denotes the i^{th} monochromatic wave emitted from the slit, and S_{mean} denotes the mean value of the current population S_i. $rand_1$ and $rand_2$ are random numbers in the range of (-1,1).

4.2. Difference-in-route update and stripe generation

Due to the different propagation distances of the two waves from FS and SS, the wave with an even multiple of half-wavelength optical path difference will undergo constructive interference (CI), while the wave with an odd multiple of half-wavelength optical path difference will undergo destructive interference (DI). YDSE simulates the behavior of the CI and the DI and the path of each wave to reach the screen. This position update model is defined as:

$$X_i = (\frac{FS_i + SS_i}{2}) + \Delta L \tag{15}$$

$$\Delta L = \begin{cases} 0 & ,if \ \ CI \ occurs \ at \ m = 0 \\ (2m+1)\dfrac{\lambda}{2} & ,if \ \ CI \ occurs \ at \ odd \ m \\ m\lambda & ,if \ \ CI \ occurs \ at \ even \ m \end{cases} \tag{16}$$

where *λ* is the wavelength, *m* is the ordinal number of the fringes and *m*=*i*-1, and *ΔL* is the optical range difference between FS_i and SS_i, which can be defined by Equation (16). The generated light wave projected onto the screen will generate interference fringes, and the nature of the fringes is different for different serial numbers *m*. Specifically, as shown in Figure. 1. *m*=0 corresponds to the central bright stripe, *m* corresponds to the dark stripe when *m* is an odd number, and *m* corresponds to the bright stripe when *m* is an even number.

4.3. Amplitude updating mechanism

YDSE effectively simulates the difference in amplitude at CI and DI , the mathematical model for this behavior is as follows:

$$A_{bright}^{t+1} = \frac{2}{1+\sqrt{\left|1-\beta^2\right|}} \tag{17}$$

$$\beta = \frac{t}{T}\cosh\left(\frac{\pi}{t}\right) \tag{18}$$

$$A_{dark}^{t+1} = \delta \times \tanh^{-1}\left(-\frac{t}{T}+1\right) \tag{19}$$

$A^{t+1}{}_{bright}$ and $A^{t+1}{}_{dark}$ represent the average amplitude of the light wave at the bright pattern and at the dark pattern at iteration up to t+1 times, respectively, t is the current iteration number, and T is the maximum iteration number.

4.4. Exploration phase

This stage is oriented to the area where DI occurs. In order to explore the potential better solution in the dark pattern, YDSE provides the following position update strategy, so that the solution moves in the dark pattern and finally approaches the central light pattern:

$$X_{m_{odd}}^{t+1} = X_{m_{odd}}^{t} - (r_1 \times A_{dark}^{t+1} \times Int_{m_{odd}}^{t+1} \times X_{m_{odd}}^{t} - z \times X_{best}^{t}) \tag{20}$$

$$Int_{m_{odd}}^{t+1} = Int_{\max}^{t+1} \times \cos^2\left(\frac{\pi d}{\lambda L} y_{dark}^{t+1}\right) \tag{21}$$

$$Z = \frac{a}{H} \tag{22}$$

$$a = t^{2\times r_2 - 1} \tag{23}$$

where $X^{t}{}_{best}$ is the optimal solution at iteration to t, $X^{t+1}{}_{modd}$ is the position of the new m^{th} dark streak at iteration to t+1, and $X^{t}{}_{modd}$ is the position of the old m^{th} dark streak at the iteration up to t. $Int^{t+1}{}_{modd}$ represents the light intensity of the m^{th} dark streak at t+1, and it can be computed by Eq. (20) where $y^{t+1}{}_{dark}$ is the distance of this dark streak from the central distance of the bright streak. Z is the test vector in *Dim* dimension, which can be calculated by Eqs. (21)(22). a is a random value in the range of [-T,T], and H is a random vector defined between [-1,1]. r_1 and r_2 are both random numbers in the range of [0,1].

4.5. Development phase

This phase is oriented towards the region where the CI occurs, the bright stripe is considered to be the more promising interval to contain the optimal solution, and the YDSE develops all the regions in the bright stripe that are potentially optimal solutions. Therefore, the location update strategy for bright stripe intervals is defined as:

$$X_{m_{even}}^{t+1} = X_{m_{even}}^{t} - ((1-g) \times A_{bright}^{t+1} \times Int_{m_{even}}^{t+1} \times X_{m_{even}}^{t} + g \times (Y)) \tag{24}$$

$$Y = X_{m_{rand1}}^{t} - X_{m_{rand2}}^{t} \tag{25}$$

$$Int_{m_{even}}^{t+1} = Int_{\max}^{t+1} \times \cos^2(\frac{\pi d}{\lambda L} y_{bright}^{t+1}) \tag{26}$$

$X^{t+1}{}_{meven}$ is the position of the new m^{th} bright stripe at iteration up to t+1, and $X^{t}{}_{meven}$ is the position of the old m^{th} bright stripe at iteration up to t. $Int^{t+1}{}_{meven}$ represents the light intensity of the m^{th} bright stripe at t+1, and it can be calculated by Eq. (25), where $y^{t+1}{}_{bright}$ is the distance between this bright stripe and the central bright stripe, and $Int^{t+1}{}_{max}$ is the maximum light intensity detected at iteration up to t. Y is the distance between two randomly selected stripes, either bright or dark. g is a random value belonging to [-1,1]. Eventually, all the solutions for the dark and bright stripes will converge to the central bright stripe region. Then the position update strategy that occurs in the central bright stripe is:

$$X_{m_{zero}}^{t+1} = X_{best}^{t} + (A_{bright}^{t+1} \times Int_{\max}^{t+1} \times X_{m_{zero}}^{t} - r_3 \times z \times X_{r_b}^{t}) \tag{27}$$

$$Int_{\max}^{t+1} = C \times q \tag{28}$$

$$q = \frac{t}{T} \tag{29}$$

where $X^{t+1}{}_{mzero}$ determines the position of the new central bright stripe for the t+1 iteration, and $X^{t+1}{}_{mzero}$ is the current position of the central bright stripe. $X^{t}{}_{rb}$ is the position of the randomly selected bright stripe, and r_b is an even and integer number. r_3 is a random number in the range of [0,1], q is a number that increases with iteration, and C is the light intensity increase factor, which is a constant.

5. Textile dyeing formulation optimization model

In this section, the optimization model of textile dyeing formulation will be constructed based on the K- M optical model introduced in the previous section and the color difference theory of CIELAB uniform color space, and solved using the YDSE optimizer.

5.1. Construction of textile color matching optimization model

Considering red, yellow and blue dyes in this study, a set of color matching scheme can be defined as:

$$\Omega = \{M, m_{red}, m_{yellow}, m_{blue}\} \tag{30}$$

Where M is the mass of the substrate, m_{red} is the mass of the red dye, m_{yellow} is the mass of the yellow dye, and m_{blue} is the mass of the blue dye, all in kg. then the concentration of the three dyes relative to the substrate can be defined as:

$$c_{red} = \frac{m_{red}}{M} \quad c_{yellow} = \frac{m_{yellow}}{M} \quad c_{blue} = \frac{m_{blue}}{M} \tag{31}$$

Although the actual measured K/S value has a nonlinear relationship with concentration, within a certain concentration range, the linear relationship assumed by the colorant mixing and summation model is established. Since this research focuses more on solving the problem of optimal color scheme, so the linear equation was used to fit the relationship between K/S value and c_i. Thus, the K/S values of the three dyes can be obtained from the following equation:

$$(\frac{k}{s})_{\lambda}^{i} = \alpha_{\lambda}^{i} c_i + \beta_{\lambda}^{i} \tag{32}$$

where $\alpha^{i}{}_{\lambda}$ and $\beta^{i}{}_{\lambda}$ are both parameters of the linear fitting equation for dye i at wavelength λ, and c_i is the relative concentration of this dye. Substituting the above equations into Eq. (6), the K/S value at wavelength λ of the sample using this color matching scheme Ω can be calculated:

$$(\frac{K}{S})_{\lambda}^{\Omega} = (\frac{K}{S})_{\lambda}^{0} + \sum_{i=1}^{3} c_i(\alpha_{\lambda}^{i} c_i + \beta_{\lambda}^{i}) \tag{33}$$

Then the reflectance $R^{\Omega}(\lambda)$ of this sample at λ can be calculated according to equation (7):

$$R^{\Omega}(\lambda) = 1 + (\frac{K}{S})_{\lambda}^{\Omega} - \sqrt{(\frac{K}{S})_{\lambda}^{\Omega^2} + 2(\frac{K}{S})_{\lambda}^{\Omega}} \tag{34}$$

Therefore, the color parameters L^{Ω}, a^{Ω}, and b^{Ω} of the sample can be calculated by Eqs. (8)(9)(10), and the color parameters L^{T}, a^{T}, and b^{T} of the target sample T can be calculated at the same time. The color difference between the sample using the color scheme Ω and the target sample T can be calculated by Eq. (11), that is, the difference between the current color scheme and the target color:

$$\Delta E_T^{\Omega} = [(L^{\Omega} - L^{T})^2 + (a^{\Omega} - a^{T})^2 + (b^{\Omega} - b^{T})^2]^{\frac{1}{2}} \tag{35}$$

This study ignores the differences in dye costs and is oriented towards the need for color consistency, such an objective is of practical relevance for the current production process. Therefore, the process of finding the optimal color matching scheme aims at finding a set of Ω with minimum color difference from T, which can be constructed as a constrained optimization problem:

$$\begin{aligned} &minimize\ \ \Delta E_T^{\Omega}(M, m_{red}, m_{yellow}, m_{blue}) \\ &s.t.\ \ \begin{cases} M = M_0 \\ M, m_{red}, m_{yellow}, m_{blue} > 0 \end{cases} \end{aligned} \tag{36}$$

5.2. Algorithm implementation for solving the textile color matching optimization problem

In this study, the Young's Double-Slit Interference Optimizer (YDSE) is used to solve the optimization problem of color matching scheme. According to the constrained optimization problem, the fitness function selected in this paper is: $fitness(x)=(\Delta E^{\Omega}{}_{T} + \delta)^{-1}$, δ is a constant that avoids the denominator to be 0, and takes the value of 10^{-7}. Satisfying that the smaller the color difference is, the larger the value of fitness is, the closer the solution is to the optimal solution. Based on the above scheme, the flowchart of the algorithm implementation in this study is shown as Figure 1.

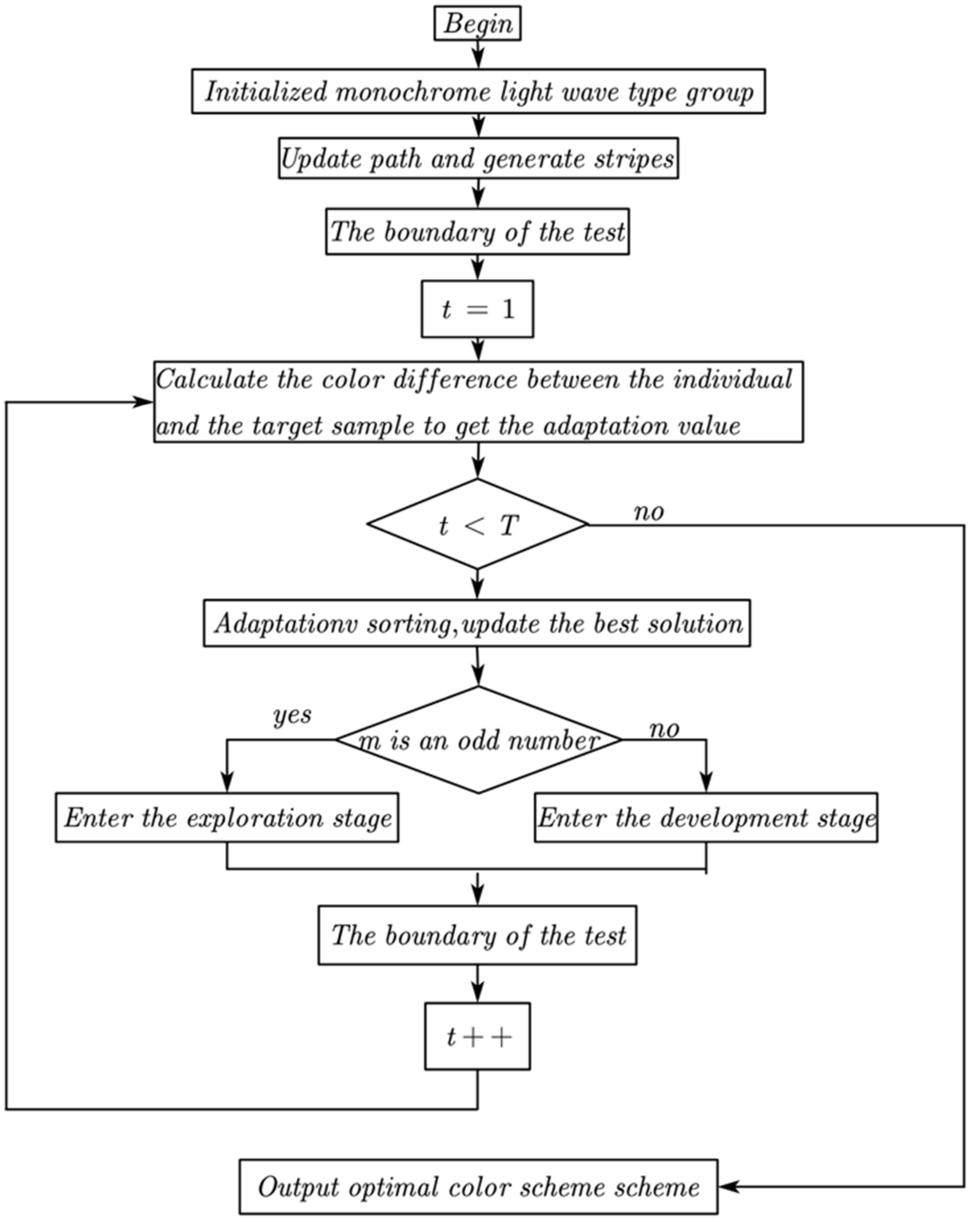


Figure 1. YDSE algorithm color matching flow

6. Experiment and Analysis

6.1. Experimental preparation

In this paper, 12 textile dyeing target samples were prepared according to randomized formulations (all of which were mixed with red, yellow and blue dyes) and their spectral reflectance $R(\lambda)$ was measured at 400 *nm*-700 *nm* using a spectral analysis device with a wavelength interval $\Delta\lambda$ of 20 *nm*. Meanwhile, the three dyes were measured at concentrations of 0.05, 0.1, 0.5, 1, 2, 3, 4, 5, respectively. K/S values at wavelength range 400 *nm*-700 *nm* ($\Delta\lambda$=20 *nm*). MATLAB R2021a was used for experiments and calculations in this study, and all experimental results were obtained on the same computer (MacBook Pro, Intel Core i5).

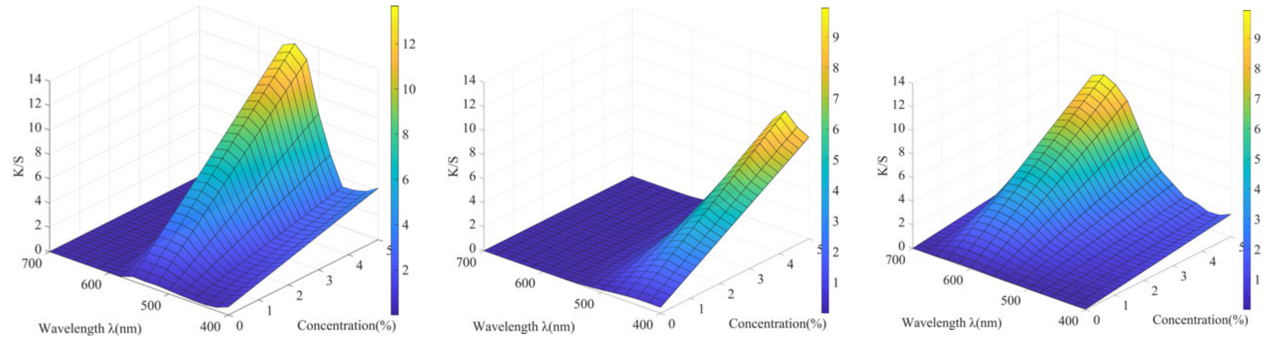
6.2. Measurement and processing of experimental samples

The three parameters L^T, a^T, and b^T of the samples in the CIELAB uniform color space were calculated based on the measured spectral reflectance $R(\lambda)$ and recorded in Table 1.

Table 1. Parameters of samples in CIELAB uniform color space L^T, a^T, b^T

No.	L^T	a^T	a^T
#1	76.9813	20.2190	14.3529
#2	85.5258	4.4114	1.2128
#3	80.3563	-3.9168	-8.6918
#4	74.8427	-5.1401	-0.0343
#5	72.4633	-1.3333	14.5867
#6	79.5739	2.4417	-3.1428
#7	65.7879	16.0158	-11.9986
#8	73.2544	-6.2272	-14.1366
#9	82.2065	14.0835	11.1348
#10	87.3058	7.9977	34.3120
#11	86.8205	-2.8047	7.8499
#12	69.1224	-6.0723	6.8235

The K/S values of red, yellow and blue dyes at different wavelengths as well as the dye concentrations were linearly fitted, respectively, and the obtained parameters $\alpha^i{}_\lambda$, $\beta^i{}_\lambda$ and R^2 are shown in Table 2, and the R^2 of regression equations are all greater than 0.98, indicating that the linear fit is excellent and can be used for subsequent experiments.



(a) Red (b) Yellow (c) Blue

Figure 2. Relationship between K/S value, concentration and wavelength for red, yellow and blue dyes

Table 2. Fitting results of K/S values of dyes with concentration at different wavelengths

λ	$\alpha^{red}{}_\lambda$	$\beta^{red}{}_\lambda$	R^2	$\alpha^{yellow}{}_\lambda$	$\beta^{yellow}{}_\lambda$	R^2	$\alpha^{blue}{}_\lambda$	$\beta^{blue}{}_\lambda$	R^2	$(K/S)^0{}_\lambda$
400	0.714	0.658	0.994	1.591	0.488	1.000	0.371	0.049	0.990	0.039
420	0.667	0.280	0.990	1.691	0.499	1.000	0.293	0.020	1.000	0.026
440	0.638	0.161	0.989	1.891	0.489	1.000	0.283	0.018	1.000	0.018
460	0.621	0.180	0.997	1.701	0.423	1.000	0.363	0.016	1.000	0.015
480	1.071	0.230	0.999	1.291	0.327	1.000	0.393	0.018	1.000	0.011
500	1.668	0.293	1.000	0.841	0.212	1.000	0.539	0.035	0.999	0.010
520	2.468	0.359	1.000	0.391	0.113	0.999	0.679	0.039	1.000	0.008
440	2.668	0.335	1.000	0.149	0.048	1.000	0.880	0.034	0.999	0.007
560	2.568	0.379	1.000	0.059	0.024	0.999	1.280	0.036	1.000	0.006
580	1.073	0.046	0.999	0.024	0.010	0.982	1.675	0.057	0.999	0.006
600	0.233	0.012	0.996	0.007	0.005	1.000	1.875	0.064	1.000	0.005
620	0.050	0.009	1.000	0.002	0.002	0.999	1.971	0.069	1.000	0.005
640	0.010	0.007	0.999	0.001	0.002	1.000	1.895	0.060	1.000	0.005
660	0.005	0.005	1.000	0.001	0.002	1.000	1.280	0.029	1.000	0.004
680	0.002	0.007	0.987	0.000	0.002	0.999	0.493	0.018	1.000	0.004
700	0.001	0.006	0.926	0.000	0.002	0.998	0.343	0.005	1.000	0.004

The relationship between K/S value, concentration, and wavelength for the three dyes is shown in Figure. 2. It can be found that the relationship between the K/S value of any dye at any wavelength and the concentration of the dye is linear. Figure. 3. shows the distribution of K/S values with wavelength (i.e., the cross section of the three eigen-surfaces in Fig. 2. at c_i=0.5, c_i=1, and c_i=2) for the three dyes at concentrations of 0.5, 1, and 2. For the same dye, the K/S values at concentration 0.5 are smaller and distributed in the inner circle of the image, while the K/S values at concentration 2 are larger and distributed in the outer circle of the image. The three dyes have distinctly different regions of response to wavelengths, which can be used to make up the raw material for color matching in textiles.

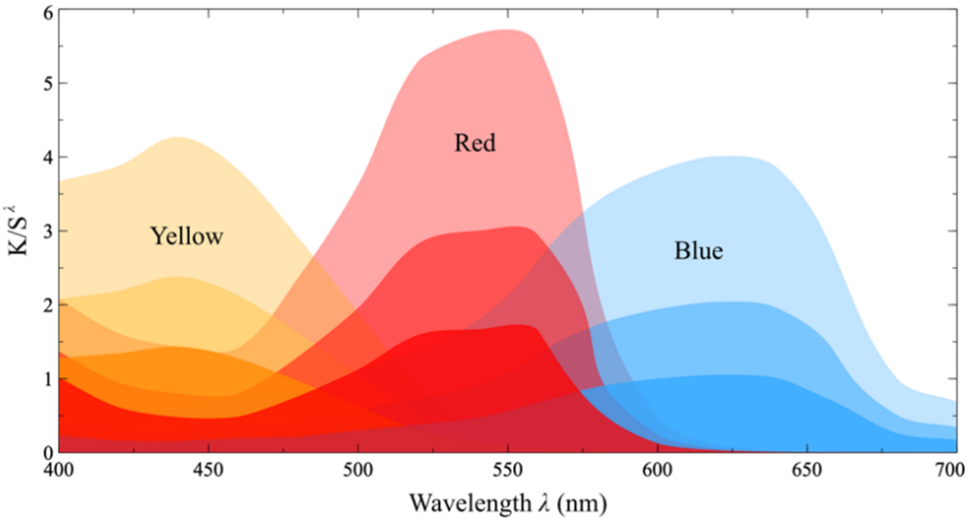


Figure 3. Distribution of K/S values by wavelength for three dyes

6.3. Selection of YDSE parameters

Some of the YDSE model parameters in this study are selected with reference to the original paper. Since the number of light waves *NP* and the number of iterations *T* have a large impact on the convergence of the algorithm, in order to verify the convergence performance of the algorithm, this paper takes sample #1 as the experimental object, and takes the values of *NP* and *T* several times, and uses the final color difference *ΔE* and the convergence time *τ* as the experimental results and analyzes them. The results are shown in Table 3. The color difference is already close to 0 when the seventh set of parameters is chosen, and the model converges faster, which is applicable to the study of this paper.

Table 3. Algorithm parameters debugging and convergence analysis

parameters	parameter debugging							
	1	2	3	4	5	6	7	8
NP	30	30	50	50	100	100	100	100
T	50	100	100	200	200	400	600	800
ΔE	1.314	0.188	0.133	0.0096	0.0034	9.88E-05	7.27E-07	6.37E-08
τ(s)	0.018	0.025	0.033	0.059	0.106	0.196	0.289	0.364

The specific parameters of YDSE were set as follows: *λ*=5×10-6, *I*=0.01, *L*=1, *d*=5×10-3, *δ*=0.38, *C*=10-20, *NP*=100, *T*=600.

6.4. Experimental results and analysis

In this experiment, the mass of substrate *M*=2*kg* was fixed. The optimization of the formulations for 12 samples was solved using YDSE optimizer and the results obtained are shown in Table 4. Comparing the three parameters $L^Ω$, $a^Ω$, $b^Ω$ of the output optimal formula with those of the original samples in Table (1), it can be seen that the color of the optimal formula is very close to the real color, and the color difference ΔE is in the order of 10^{-6} or even 10^{-7}. The error distributions of L^{Ω}, a^{Ω}, and b^{Ω} are shown in Figure. 4. They are all in the range of -2×10^{-3} and 2×10^{-3}, concentrated at 0, and the optimization effect is better.

Table 4. Optimal formulation of samples, L^{Ω}, a^{Ω}, b^{Ω}, ΔE

No.	m_{red}	m_{yellow}	m_{blue}	L^{Ω}	a^{Ω}	b^{Ω}	ΔE
#1	0.6004	0.6892	0.1330	76.9814	20.2188	14.3530	7.27E-07
#2	0.2046	0.1448	0.2812	85.5256	4.4133	1.2148	5.16E-06
#3	0.0753	0.0669	0.6777	80.3556	-3.9178	-8.6929	4.27E-06
#4	0.1452	0.4609	0.8380	74.8416	-5.1401	-0.0352	1.35E-06
#5	0.2693	0.9685	0.7637	72.4632	-1.3322	14.5864	4.43E-07
#6	0.2814	0.1929	0.5356	79.5739	2.4417	-3.1428	6.93E-07
#7	0.9122	0.1088	0.7901	65.7879	16.0158	-11.9986	5.08E-07
#8	0.0223	0.0891	1.0544	73.2541	-6.2272	-14.1369	7.49E-07
#9	0.3912	0.4471	0.1250	82.2065	14.0835	11.1348	9.81E-07
#10	0.0230	0.9100	0.0040	87.3058	7.9977	34.3120	1.45E-06
#11	0.0129	0.3014	0.3395	86.8205	-2.8047	7.8499	1.51E-06
#12	0.1922	0.8745	1.0409	69.1224	-6.0723	6.8235	1.70E-06

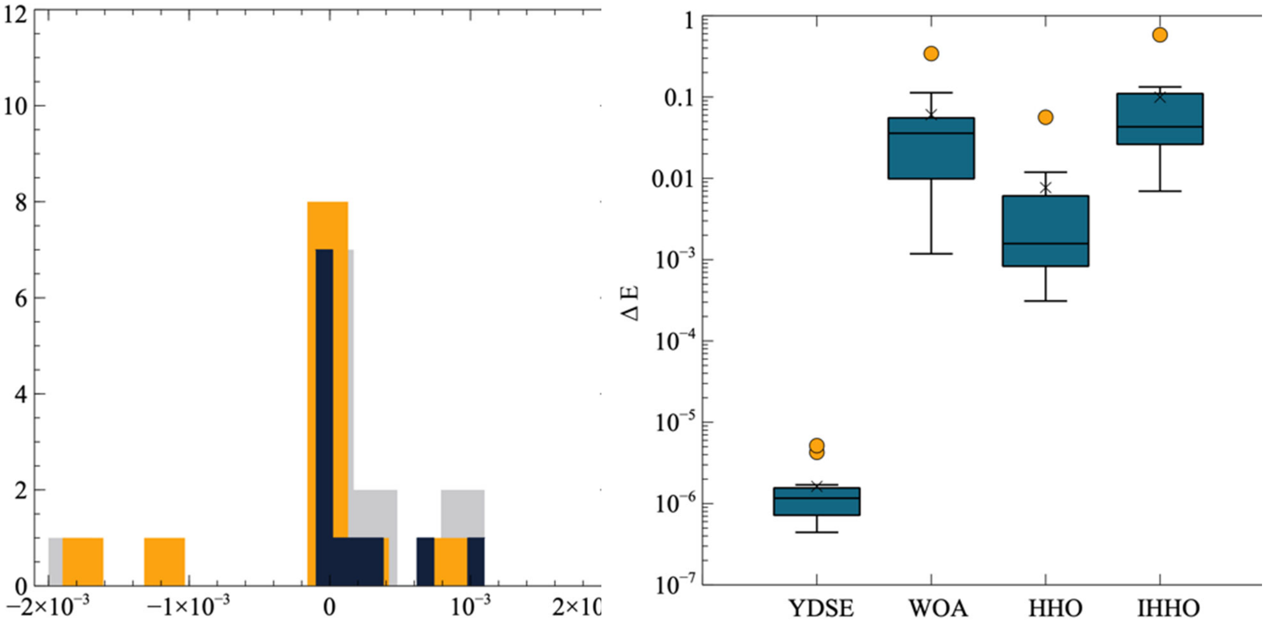


Figure 4. L^{Ω}, a^{Ω}, b^{Ω} error distribution (left) and comparison of the four algorithms' solution results (right)

In order to confirm the reliability of the YDSE algorithm, the Whale Optimization Algorithm (WOA), Harris Hawk Optimization Algorithm (HHO), and Improved Harris Hawk Optimization Algorithm (IHHO) are selected to solve the optimal formulations from sample #1 to sample #12, and the results are shown in Table 5. Statistical analysis of the data in the table is shown in Figure. 4. It can be seen that the optimal color scheme solved by YDSE is more superior, and its color difference is of an order of magnitude much smaller than that of several other algorithms of 10^{-2} or 10^{-3}.

Table 5. Comparison of algorithmic solving effects

No.	YDSE	WOA	HHO	IHHO
#1	7.27E-07 *	5.52E-02	1.64E-03	7.37E-03
#2	5.16E-06 *	1.18E-03	5.83E-03	1.07E-01
#3	4.27E-06 *	1.80E-02	7.75E-04	1.33E-01
#4	1.35E-06 *	1.22E-02	3.10E-04	2.93E-02
#5	4.43E-07 *	2.91E-03	1.19E-02	2.67E-02
#6	6.93E-07 *	2.41E-03	8.49E-04	5.68E-02
#7	5.08E-07 *	5.61E-02	7.66E-04	5.82E-01
#8	7.49E-07 *	1.13E-01	5.64E-02	1.20E-01
#9	9.81E-07 *	3.56E-02	9.28E-04	2.46E-02
#10	1.45E-06 *	3.61E-02	4.46E-03	7.52E-02
#11	1.51E-06 *	3.42E-01	1.51E-03	2.73E-02
#12	1.70E-06 *	5.32E-02	6.88E-03	6.95E-03
Average	1.63E-06 *	6.07E-02	7.69E-03	9.97E-02

7. Conclusion

In this paper, the optimization problem of textile color matching scheme is constructed based on the K- M optical model and the theory of chromatic aberration in the uniform color space of CIELAB, and solved by using the newly proposed Young's Double-Slit Interference Optimizer (YDSE) in 2023. The experimental results demonstrate that YDSE performs superiorly in the optimization problem of color matching scheme, the output optimal formulation has a very small difference with the original sample, and the algorithm converges faster, which meets the current demand of industrial production. Compared with manual color matching, YDSE intelligent color matching has less time and material costs, and can create higher value for manufacturing enterprises with equal inputs.

This study focuses on the problem of color matching optimization for opaque textiles, and although some results have been achieved, there are still some problems that need to be improved. This paper is based on the K-M theory and the color addition and mixing model as the theoretical foundation and subsequent research, which only considers the linear region of dye K/S value and concentration, while the actual situation of production is more complicated. The follow-up work can improve the working performance of intelligent algorithms in the field of color matching from the perspectives of chemical properties and optical properties of dyes. Meanwhile, future research can consider the cost of dyes, scale efficiency, etc., which constitutes a multi-objective optimization problem, in order to bring the distance between theory and real production closer.

References

[1] Guan Xuemei, Yang Qusan, Wu Yan. Research on Wood Staining and Color Matching Algorithm Based on Improved Grey Wolf Optimizer-Based SVR[J]. China Forest Products Industry, 2023, 60(7).

[2] Ding Man, YUAN Yunlei, ZHANG Xinxin, et al. Product color emotional design based on deep learning[J]. Computer Integrated Manufacturing Systems, 2023, 29(5): 1647.

[3] Jianguo R ,Heng L ,Jiqing L . The color matching design based on polynomial regression[J]. Textile Research Journal,2022,92(7-8).

[4] Sun Xianqiang, Xue Yuan, Liu Yuexing, et al. A neural network algorithm and its prediction model towards the full color phase mixing process of colored fibers[J]. Textile Research Journal, 2023, 93(1112):2449-2463.

[5] Gao Jiale,Ma Lingkun,Sun Shuang. Fur color matching method based on chaotic sparrow algorithm[J]. Leather Science and Engineering,2023,33(05):22-26.

[6] GUAN Xuemei,HUANG Jingyi,XU Baocheng et al. Research on full-spectrum wood color matching algorithm based on particle swarm optimization Stearns-Noechel model[J]. Forest Industry,2022,59(05):20-26.

[7] H. Chen, "Research on Ink Color Matching based on Stearns Noechel and BBO Optimization Algorithm," 2021 5th Asian Conference on Artificial Intelligence Technology (ACAIT), Haikou, China, 2021, pp. 336-339.

[8] Zhang Ge. Research on ink color matching combining Stearns-Noechel and BBO optimization algorithm [D]. Xi'an University of Technology,2019.

[9] Alcaraz de la Osa R, Iparragirre I, Ortiz D, et al. The extended Kubelka–Munk theory and its application to spectroscopy[J]. ChemTexts, 2020, 6: 1-14.

[10] WANG Zhuo,YANG Ruihua,PAN Bo et al. Color matching model of color-spun yarn based on Kubelka-Munk double constant theory[J]. Cotton Textile Technology,2021,49(02):24-30.

[11] Moussa A. Textile color formulation using linear programming based on Kubelka-Munk and Duncan theories[J]. Color Research & Application, 2021, 46(5): 1046-1056.

[12] Wang LJ. Research on blending color measurement based on CIELAB uniform color space and clustering algorithm [D]. Zhejiang University of Technology, 2011.

[13] Şahin Cenk,Balcı Onur,Işık Melek, et al. Artificial neural networks approach for prediction of CIELab values for yarn after dyeing and finishing process[J]. The Journal of The Textile Institute,2023,114(9).

[14] Mohamed A,Doaa E,Mohammed J, et al. Young's double-slit experiment optimizer : A novel metaheuristic optimization algorithm for global and constraint optimization problems[J]. Computer Methods in Applied Mechanics and Engineering,2023,403(PA).