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RESEARCH ARTICLE

Regularized Extreme Learning Machine Based on Remora Optimization Algorithm for Printed Matter Illumination Correction

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ABSTRACT In the process of printed matter quality inspection, the influence of lighting conditions leads to a large color difference between the captured image and the actual image. Therefore, this paper proposes an illumination correction model based on Remora Optimization Algorithm for Regularized Extreme Learning Machine (ROA-RELM). First, the algorithm extracts the statistical features of the printed matter image using the Grey-Edge framework. Next, the statistical features are used as inputs to the Regularized Extreme Learning Machine (RELM). Then, the remora algorithm (ROA) is used to optimize the weights w and bias b of the input layer of the RELM, which improves the prediction accuracy. At last, the image is corrected by color constancy algorithm based on the output. In order to verify the effectiveness of the algorithm proposed in this paper, the method of color difference detection is used in this paper to evaluate the effect of the illumination correction algorithm on the detection of the color quality of printed matter. The experimental results show that the algorithm mentioned in this paper can effectively improve the presentation of printed matter images, and the angle root-mean-square error is reduced by 11.04% compared with the control group's illumination-corrected model.

INDEX TERMS Illumination correction, printed matter, remora optimization, regularized extreme learning machine.

I. INTRODUCTION

Plastic flexible packaging printing refers to the use of printing technology to print ink on plastic film and other plastic flexible packaging materials on the process. In China, the plastic flexible packaging industry generally use intaglio printing. Plastic flexible packaging gravure printing is mostly multi-batch printing and high-volume printing, control the chromatic deviation of the same batch of prints is relatively difficult. The most common quality defects in the printing process are color deviations between the printed image and the sample and color variations in the printing process. Therefore, the quality inspection for printed materials is particularly important. The application of artificial intelligence technology in the online inspection system of print quality can realize the efficient inspection of print quality and improve the inspection speed and accuracy. However, the online inspection system for printed matter quality still suffers from a number of problems such as light source selection and poor image quality. In addition, in the actual production environment, due to uneven illumination, printed matter reflections and other problems, it will make the image captured by the camera and the actual image differences, seriously affecting the detection results of the system. Therefore, the use of machine learning to achieve automatic and efficient illumination correction and accurate estimation of the illumination information of an image is essential to improve the detection accuracy of the system.

In recent years, machine learning has been widely used in the fields of healthcare [1], [2] and IoT [3], and the

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application of machine learning to illumination correction has also been widely studied. In order to obtain a functional mapping relationship between the sample image and the corresponding illumination, Cardei et al. [4] proposed a simple method to estimate the illumination of an image based on an error back propagation neural network, which can continuously adjust the network parameters through back propagation in order to make the loss function decreasing until the stopping condition is reached. However, for traditional neural networks, it takes a lot of time for training and parameter optimization, and it is also easy to fall into local minimum value, slow convergence of the algorithm and other disadvantages [5]. Compared to traditional neural networks, Extreme Learning Machines (ELM) [6] have faster training speeds and good generalization capabilities, do not require complex hierarchical structures or back-propagation algorithms, and use stochastic initialization of weights and biases, which greatly simplifies the implementation and application of the model. Li et al. [7] proposed a supervised combination strategy for illumination chromaticity estimation, and the algorithm effectively overcame the shortcomings of traditional neural networks that are easy to fall into local extremes. Xiong et al. [8] used support vectors (SVR) instead of neural networks to estimate the chromaticity of scene illumination, thus achieving color constancy in the color imaging system of a digital camera. This method can effectively eliminate the effect of scene illumination on the image color and restore the color of the image by accurately estimating the chromaticity of the scene illumination.

Although there has been some progress in the research of illumination correction algorithms, these above studies are more based on public datasets and have fewer practical applications. Researchers are beginning to explore the application of illumination correction in practice and are starting to use intelligent optimization algorithms to optimize the traditional algorithms.

Zhou et al. [9] proposed a textile illumination correction model based on a rotating forest-based online sequential extreme learning machine (RF-DE-OSELM), which optimizes the input layer weights and biases of the neural network by a differential evolutionary algorithm, and then uses DE-OSELM as the base learner, and uses a random forest algorithm (RF) to integrate the different base learners, which greatly improves the model's accuracy and robustness. Liu and Yang [10] optimized random vector links by improving marine predators to compute the color constancy of dyed fabrics, which in turn eliminates the effect of light variations on the color difference classification of dyed fabrics. Zhang et al. [11] proposed an illumination correction algorithm based on improved least squares support vector machine regression (LSSVR) and improved gray GM (1,1) model, aiming at solving the problem of color constancy of textiles under light conditions. Since LSSVR is prone to the fall into the disadvantage of global optimization, the algorithm compensates for this by the local optimization ability of the GM (1,1) model. Experimental results show that the algorithm is stable and provides good illumination compensation. Wang et al. [12] proposed a illumination correction model for support vector (OBL-IWOA-SVR) based on the whale algorithm improved by oppositional learning strategy, aiming at solving the problem that underwater images under different light sources will produce chromatic deviation, and the experiments proved that the proposed model has a better illumination correction effect than the rest of the models through various measurements such as box plots, histograms, and Wilcoxon's symbolic rank sum test. Ren [13] in the study of printing defect methodology eliminates the effect of illumination on image quality by performing gray scale transformation, image enhancement and image registration on the captured image after image acquisition. Although this algorithm can eliminate the effect of illumination on image quality to a certain extent, it generates information loss during the gray scale transformation process, which leads to the loss or confusion of details in the image. Wang et al. [14] proposed an image correction method based on light reflection model and multi-scale theory for low illumination image enhancement. By separating the illumination components, adaptively adjusting the parameters of the enhancement function, and fusing the details, the method can improve the quality of low-lighting images, which can be significantly enhanced in terms of brightness and contrast. This image correction method has practical application value for the processing of low illumination images and produces clear, bright and natural image results. Zhou et al. [15] proposed an illumination correction algorithm based on Extreme Learning Machine (ELM) for dyed fabrics in order to eliminate the influence of scene illumination on the evaluation of color difference of dyed fabrics and combined with the Gray Wolf Optimizer (GWO) and Ant Lion Optimizer (ALO) for the Optimization. The features of the dyed fabric image are extracted as input vectors using the Gray Edge framework, which include the texture, edges, and other information of the dyed fabric, and then the Gray Wolf Optimizer (GWO) is used to provide a set of optimized initial populations for the Ant-Lion Optimizer (ALO). The GWO algorithm is used to improve the optimization finding ability of the ALO algorithm for better optimization of the parameters of the ELM. The parameters of the ELM are optimized using the improved ALO algorithm. Finally, the illumination of the dyed fabric is corrected using the proposed GWO-ALO-ELM algorithm and the image is restored to the effect display under standard illumination using a diagonal discount model. In summary, these algorithms provide different methods and techniques in illumination correction research in the textile and printed matter domains. They address the effects of illumination variations on image quality and color accuracy by optimizing weights, integrating base learners, and improving optimization algorithms to improve the effectiveness and performance of illumination correction models. However, with further updates of the intelligent optimization algorithms, the performance of the algorithmic models is further improved. The introduction

TABLE 1. Effect of factory environment on illumination.

Factor	Effect	Effect on illumination
Lighting equipment	Produces different spectra and brightness	Changes in uniformity and intensity of illumination
Cargo stacking	Cast a shadow	Lack of illumination and uneven illumination distribution
Light reflection object	Reflection or refraction	Unstable illumination changes
Pollution and dust	Absorbs or scatters light	Changes in the clarity and brightness of the illumination

TABLE 2. The effect of illumination conditions on the image presentation effect of plastic flexible packaging.

Factor	Effect	Impact on the image
Color temperature of illumination	Affects color accuracy	Image color deviation
Illumination intensity	Affecting contrast	Loss of image detail or blurring
Illumination angle	Produce shadows and highlights	Poor readability of images
Reflection of illumination	Produce glare	Deterioration of image clarity

of intelligent optimization algorithms into the field of illumination correction allows for further exploration and application of these algorithms to improve the accuracy, stability, and applicability of illumination correction. Sailfish optimizer algorithm and whale optimization algorithm were proposed in the literatures [16] and [17] respectively, based on which remora optimization algorithm was proposed by Jia et al. [18] Remora optimization algorithms are widely used in problems such as the Internet of Things [19], image segmentation [20], and medicine [21].

Most of the above studies have been applied to the textile field, where illumination correction algorithms have been extensively studied and have achieved mature applications. In the field of printed matter, changes in lighting conditions can affect the accurate color reproduction of images. For printed matter, changes in lighting conditions are not the main problem, but more important is how to ensure accurate color reproduction and color consistency of printed images. Applying light correction algorithms to printed matter can help solve the problem of color deviation and inconsistency due to different light source conditions or environmental influences. And there are relatively few studies on applying light correction models to printed matters. Therefore, it is necessary to explore and study the illumination correction algorithms for printings to meet the continuous development and application needs of color detection systems for printings. Inspired by these research results, this paper presents a remora optimized regularized extreme learning machine for illumination correction model.

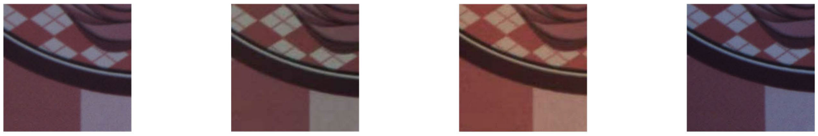
II. THE EFFECT OF ILLUMINATION CONDITIONS ON PRINTED MATTER DETECTION

In the process of printed matter quality inspection, illumination conditions are a key factor that can directly affect the quality and visualization features of the image. When using cameras for quality inspection, the illumination needs to be adjusted manually and is heavily influenced by the external light source and the physical properties of the object being measured Changes [22] in illumination can lead to changes in the brightness, contrast and color distribution of the image, which in turn affects the machine vision system's ability to recognize and analyze printings. In the actual production environment, however, many factors in the factory affect the variation of illumination, as shown in Table 1.

In summary, the actual factory production environment is more complex, which will have a certain impact on the illumination. And under different illumination conditions, the printed matter is rendered differently. When an image suffers from being too bright or too dark in uneven illumination, it can cause a loss of detail in the image [23]. Some printed matters have a reflective or glare problem, inappropriate illumination will exacerbate this phenomenon, resulting in serious discrepancies between the captured image and the actual image. Conditions such as illumination stability, uniformity, and illumination intensity all affect the effectiveness of the camera in capturing images. Taking plastic flexible packaging as an example, this paper lists the effects of several illumination conditions on its imaging effect, as shown in Table 2. Therefore, an in-depth study of the rendering effect of printing images under different illumination conditions is of great significance in determining the standardized illumination environment as well as in improving the accuracy of the printing quality inspection system.

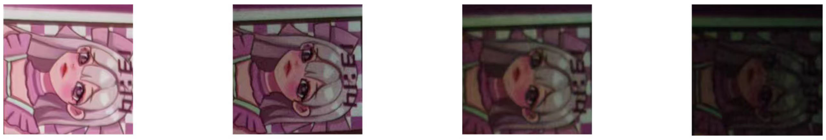
1.When using light sources with different color temperatures, the color of the captured printed matter image changes, which can lead to color differences between the captured image and the real thing, as shown in Fig. 1.

2. When capturing images of printed matter, changes in illumination intensity can have an effect on the contrast of the image. Under strong illumination, the image presents a higher contrast, while weak illumination presents a lower contrast, as shown in Fig. 2.



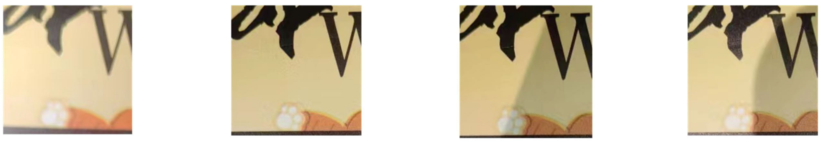
(a) (b) (c) (d)

FIGURE 1. The effect of light source color temperature on printed matter imaging.



(a) (b) (c) (d)

FIGURE 2. The effect of illumination intensity on the imaging of printed matter.



(a) (b) (c) (d)

FIGURE 3. The effect of light source direction on printed matter imaging.

(a) (b) (c) (d)

FIGURE 4. The effect of light reflection on the imaging of printed matter.

3. When capturing printed matter images, light sources at different angles will leave shadows and bright spots on the surface of the photographed object, which will affect the readability of the image content, as shown in Fig. 3.

4. When capturing images of high-gloss printed matter, the object will produce glare and diffuse reflection due to the irradiation of the light source, which will have a certain impact on the clarity and visibility of the image, as shown in Fig. 4.

In order to solve the above problems, researchers have focused on feature extraction and algorithm selection. In terms of extracting image features, in this paper, the grey edge is used to extract the chromaticity features of the printed matter image as the input vector. The grey edge framework effectively reduces the number of dimensions of the extracted features and simplifies the computation of the ROA-RELM model compared with the traditional feature extraction methods of 2D or 3D chromaticity histograms. In terms of algorithm selection, traditional neural networks have disadvantages such as complex parameter optimization and slow convergence of algorithms. Although ELM can overcome the disadvantage of traditional neural networks of falling into local extremes, its input weights and biases are randomly generated and have some instability. Zhou et al. [24] proposed a illumination correction algorithm based on Kernel Extreme Learning Machine (KELM), and the experimental results proved that the algorithm performs better than the traditional color constancy methods of SVR and ELM. However, the key and difficulty of KELM [25] lies in the selection of the kernel function and the setting of the relevant parameters. Deng et al. [26] proposed Regularized Extreme Learning Machine (RELM) based on the principle of structural risk minimization and weighted least squares, and experiments proved that the generalization performance of the RELM algorithm was significantly improved, which avoided the model from overfitting. For the input weights and biases randomly generated by RELM, this paper utilizes the advantages of remora algorithm in optimization searching to obtain the optimal weights and biases for RELM, which improves the stability and accuracy of the algorithm.

III. RELEVANT THEORIES

A. REGULARIZED EXTREME LEARNING MACHINE

The Extreme Learning Machine (ELM) is a modified single hidden layer feedforward neural network (SLFN), featuring M training samples

$\left\{(x_j, t_j), j = 1, \cdots, M\right\}, x_j = \{x_1, x_2, \cdots, x_m\}^T, t_j = \{t_1, t_2, \cdots, t_n\}^T$, x_j, $t_j$denote the input vector and the corresponding output vector of the j sample, respectively. Setting the nodes of the hidden layer to be L and the activation function to be g (w, b, x), the structure of the ELM network consists of m input neurons, L hidden neurons and n output neurons. The mathematical expression is:

$$t_j = \sum_{i=1}^{L} \beta_i g_i \left(\mathbf{w}_i \cdot \mathbf{x}_j + b_i\right) \quad j = 1, \cdots, M \tag{1}$$

$\beta_i = [\beta_{i1}, \beta_{i2}, \cdots, \beta_{iL}]^T$ denotes the weight vector connecting the i hidden neuron to the output layer, $W_i = \{W_{i1}, W_{i2}, \cdots, W_{iL}\}^T$ denotes the weight vector connecting the i hidden neuron to the input layer, and b_i denotes the bias of the i hidden node, both of which are randomly generated. The goal of the Extreme Learning Machine is to:

$$T = H\beta \tag{2}$$

Formula:

$$\boldsymbol{H} = \begin{pmatrix} g(\omega_1, b_1, x_1) & g(\omega_2, b_2, x_1) & \cdots & g(\omega_L, b_L, x_1) \\ g(\omega_1, b_1, x_2) & g(\omega_2, b_2, x_2) & \cdots & g(\omega_L, b_L, x_2) \\ \vdots & \vdots & \vdots & \vdots \\ g(\omega_1, b_1, x_N) & g(\omega_2, b_2, x_N) & \cdots & g(\omega_L, b_L, x_N) \end{pmatrix}_{M\times L} \tag{3}$$

Substituting Equation (3) into Equation. (2) is obtained by least squares and singular value decomposition:

$$\beta = \left(H^T H\right)^{-1} H^T T \tag{4}$$

The introduction of regularization coefficients improves the structural stability of the ELM and yields RELM:

$$\beta = \left(H^T H + CI\right)^{-1} H^T T \tag{5}$$

In Equation (5), C denotes the regularization factor and I denotes the unit matrix.

B. REMORA OPTIMIZATION ALGORITHM

Remora Optimization Algorithm (ROA) is a bionic-based meta-inspired algorithm inspired by the remora's ability to forage for food by adsorbing on hosts of different sizes. The remora optimization algorithm is based on randomly generating the solution locations in the feasible domain and calculating the fitness values of the solutions, and then approximating the global optimal solution through the exploration and development stages.

1) INITIALIZING POPULATIONS

The remora algorithm generates search agents in a randomized manner within a specified range, where the current position is $R_i = (R_{i1}, R_{i2}, \cdots, R_{id})$, where i denotes the number of remoras, d denotes the remora's dimension in the search space, and lb, ub denote the upper and lower boundaries, respectively.

$$R_i = lb + rand \times (ub - lb); \ \ i \in \{1, 2, \ldots, N\} \tag{6}$$

2) FREE TRAVEL (EXPLORATION PHASE)

Step1-Sailfish Strategy

When remora is connected to the sailfish, its position changes, based on the elite idea of the sailfish optimization algorithm, the remora's position is updated and the position update formula is:

$$R_i^{t+1} = R_{Best}^t - \left(rand(0,1) \times \left(\frac{R_{Best}^t + R_{rand}^t}{2}\right) - R_{rand}^t\right) \tag{7}$$

where, t denotes the current number of iterations and rand denotes the randomly selected individuals, randomly generated between 0 and 1, R_{Best}^t denotes the optimal individual. Equation (7) updates the remora's position through an optimal individual guidance mechanism. The optimal individual is the one with the best fitness value in the current iteration. The remora will use the location information of the optimal individual to guide its own location update in the hope of obtaining a better fitness value. Meanwhile, in order to maintain the diversity of the search space, a random selection strategy is also introduced in Equation (7), where an individual is randomly selected to participate in the position update process to increase the exploratory nature of the search.

Step2 - Encounter Attack

In order to determine if it is necessary to change hosts, remoras need to constantly make small movements around the host, an adaptive behavior of remoras to prevent the host from being attacked in a way that involves their own safety, calculated by the formula:

$$R_{att} = R_i^t + (R_i^t - R_{pre}) \times randn \tag{8}$$

where R_{pre} denotes the position of the individual in the previous iteration and R_{att} denotes the trial step, the mechanism utilizes the randomness of the *randn* function to perform a local search between the current position and the previous position, after which the remora determines which position to keep based on the fitness values of these two positions. With the parameter settings in Equation(7) and Equation(8), remora is able to utilize the elite idea in the sailfish optimization algorithm to update its position and take adaptive behaviors when it is under attack, which improves the algorithm's search effectiveness and adaptability.

3) EAT THOUGHTFULLY (DEVELOPMENT PHASE)

Step1-Whale Strategy

When remora is attached to a humpback whale, the attack strategy is the same as the bubble net attack strategy in WOA, and the position update formula for whale attachment is extracted based on the original WOA algorithm:

$$R_{i+1} = D \times e^{\alpha} \times \cos(2\pi\alpha) + R_i \tag{9}$$

$$\alpha = rand(0, 1) \times (\alpha - 1) + 1 \tag{10}$$

$$a = 1 - \left(1 + \frac{t}{T}\right) \tag{11}$$

$$D = |R_{Best} - R_i| \tag{12}$$

where α denotes a random number between the intervals [−1, 1] and a denotes a linear descent between the intervals [−2, −1]. When following whales, remoras can spiral the search space, effectively ensuring the algorithm's global search capability.

Step2-Host Feeding

Since the aggregation of fish is sometimes not so strong, remoras will pick up around the mouth of the host. Host feeding is a further subdivision of the exploitation process, at this stage remoras will also move around the host with the formula:

$$R_i^t = R_i^t + A \tag{13}$$

$$A = B \times \left(R_i^t - C \times R_{Best}\right) \tag{14}$$

$$B = 2V \times rand(0, 1) - V \tag{15}$$

$$V = 2(1 - \frac{t}{Max\_iter}) \tag{16}$$

where A is the movement step size, the value of which is related to the current remora dimension, and the parameter C controls the size ratio of the host to the remora and is used to reflect the remora's position.

C. FEATURE EXTRACTION BASED ON GREY-EDGE

The Grey-Edge [27] is based on the assumption made by the pixel distribution of the boundary image that the difference between the mean reflectance of the surfaces of objects in the scene is colorless. The formula for converting the color derivative of an image from RGB color space to the opposing color space is:

$$O1_x = \frac{R_x - G_x}{\sqrt{2}} \tag{17}$$

$$O2_x = \frac{R_x + G_y - 2B_x}{\sqrt{6}} \tag{18}$$

$$O3_x = \frac{R_x + G_x + B_x}{\sqrt{3}} \tag{19}$$

where R_x, G_x, B_x denote the derivatives of the response values of the three RGB color channels at the point, and $O1_x$, $O2_x$, $O3_x$ are the corresponding color derivatives at x in the opposed color space after conversion.

The Grey-Edge estimates the color of the light source by calculating the difference of the mean color in the opposing color space, and to reduce the effect of noise on the image, the algorithm introduces Gaussian smoothing preprocessing. Finally, a unified framework of unsupervised color correction algorithms is formed by generalizing the color derivatives in the opposing color space from first order to higher order:

$$(\left|\int \frac{\partial^n f^{\sigma}(x)}{\partial x^n}\right|^p dx)^{\frac{1}{p}} = ke^{n,p,\sigma} \tag{20}$$

σ is the Gaussian kernel convolution operator, p is the Minkowski paradigm, and k is a constant. $f^{\sigma}(x) = f \otimes G^{\sigma}$ denotes the convolution of the Gaussian filter to the color channel of the image. The Grey-Edge can produce many different unsupervised color constancy algorithms by simply adjusting the parameters n, p, and σ.

D. REGRESSION MODEL FOR REMORA BASED REGULARIZED EXTREME LEARNING MACHINE

Although RELM adds regularization parameters relative to ELM to enhance its generalization ability and avoid overfitting the model, the weights and biases of its input layer are still randomly generated, which is somewhat unstable. In this section, the remora optimization algorithm is used to optimize the input layer weights and biases of the RELM, and the root-mean-square error (RMSE) between the predicted and the true values of the RELM is used as the remora algorithm's fitness function, which is shown in refer to "(21),".

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(y_j - x_j\right)^2} \tag{21}$$

where y_j is the predicted value and x_j is the true value.

The block diagram of ROA-RELM algorithm program is shown in Fig. 5. The specific steps of the implementation process of the printed matter illumination correction model based on ROA-RELM are as follows:

(1) Data preprocessing: the image is processed in a certain way, and then the color features of the image are extracted as a dataset based on the grey edge, and the training set and test set are randomly divided.

(2) Parameter initialization: given the population size and the number of iterations of the ROA algorithm as well as the regularization parameters and the number of hidden neurons of the RELM algorithm, the search space range is determined.

(3) Calculate the fitness: the RMSE between the predicted value and the true value of the RELM algorithm is used as the fitness function, the lower the fitness, the closer to the optimal solution.

(4) Position update: Compare the fitness of the current position with the best fitness, if it is greater than the best fitness then move to the best fitness position, the position is updated. when the position is updated, check whether the current position exceeds the search space range, if it does, reset the current position to the search space boundary position.

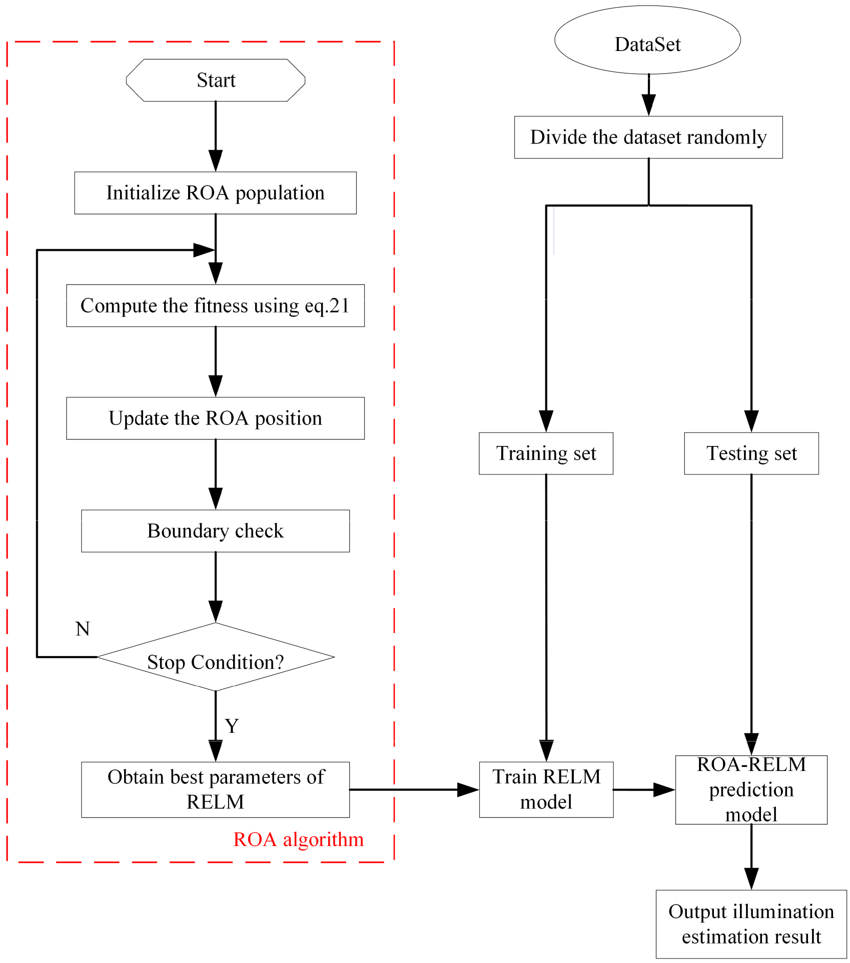


FIGURE 5. Block diagram of ROA-RELM algorithm program.

(5) Cyclic condition judgment: determine whether the current iteration satisfies the termination condition, if the termination condition is reached, pass the optimal solution obtained by the algorithm to RELM. if the termination condition is not reached, return to step (3).

(6) RELM training: bring in ROA algorithm optimized input weights and biases for training.

(7) Image correction: using the model-predicted illumination information, the image of the printing to be corrected is corrected by a color constancy algorithm.

By optimizing the population size and the number of iterations of the ROA algorithm, as well as the regularization parameters and the number of hidden neurons of the RELM algorithm, the proposed illumination correction model in this paper achieves the optimization of the algorithm performance. By adjusting these parameters, the model is able to search the optimal solution quickly, thus improving the accuracy and stability of illumination correction. In addition, the remora algorithm in this paper's model also combines the elite idea of the sailfish algorithm and the bubble net attack strategy of the whale algorithm, which provides higher flexibility and search efficiency in position updating compared with traditional intelligent optimization algorithms. This integrated optimization strategy endows the proposed model with a powerful search capability, which enables it to find the optimal solution quickly in the complex illumination correction task. Through the combination of this integrated optimization strategy, the proposed illumination correction model in this paper is able to find the optimal solution quickly, which effectively improves the accuracy of illumination correction. This provides an efficient and reliable solution for color reproduction of printed matter images.

IV. EXPERIMENTS

In this paper, a remora optimized regularized extreme learning machine based illumination correction model is proposed and its working principle is demonstrated by the experimental flow Fig 6. Firstly, 400 images of different types of printed matters were captured using an industrial camera under D65, D50, D55 and standard light sources. These images are divided into training and test sets in a certain ratio, and the chromaticity values under the current illumination conditions are measured by a spectral illuminometer, which

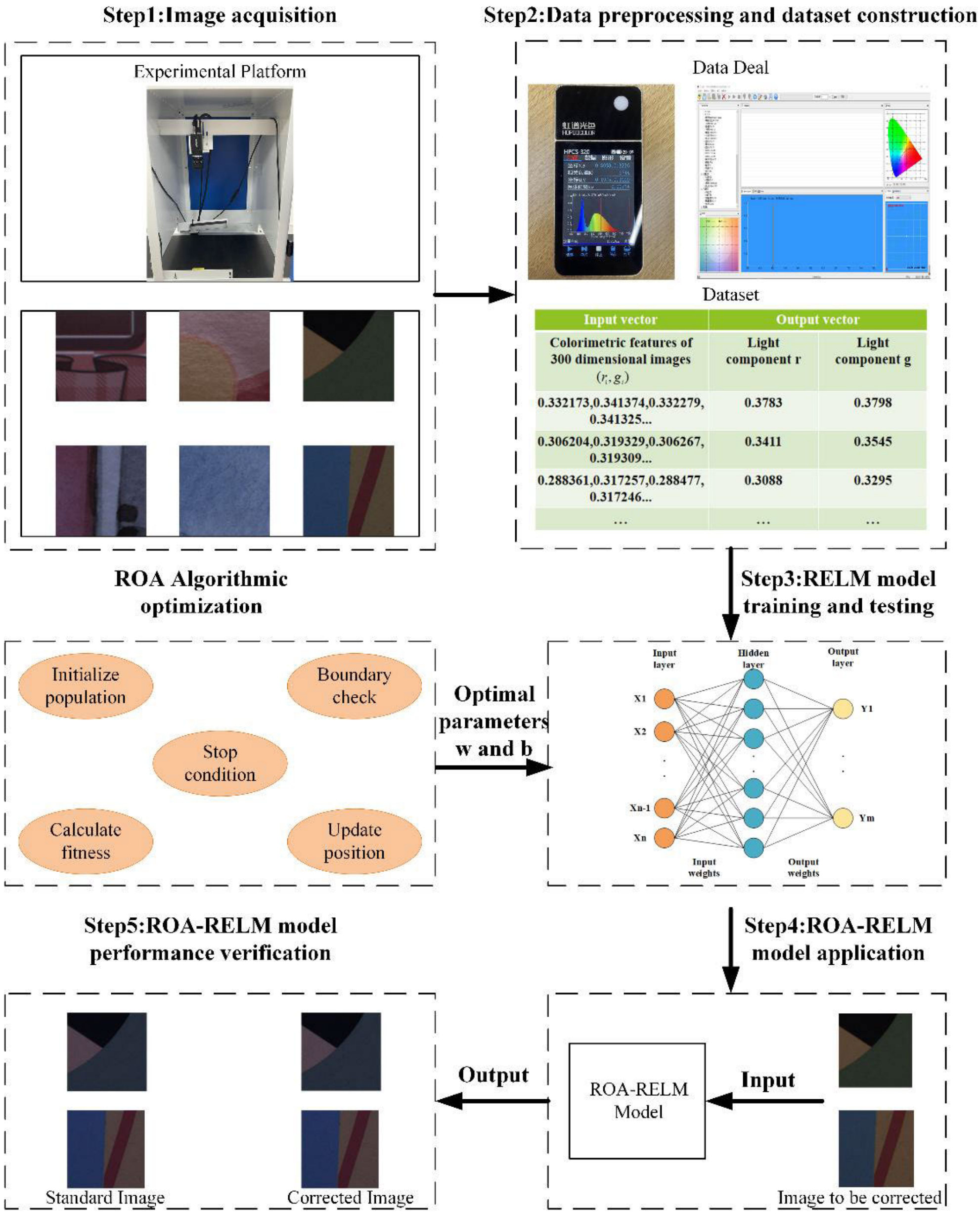


FIGURE 6. Flow chart of the experiment.

is used as the standard output of the dataset. In order to reduce the amount of data computation, this paper adopts the gray scale edge based algorithm to process the captured images and extract the color features of the images as the input vector of the training set. Compared with the traditional neural network, the extreme learning machine has faster training speed and generalization ability. In order to further improve the generalization ability of the model and avoid overfitting, this paper adopts the regularized extreme learning machine proposed based on the principle of structural risk minimization. In the regularized extreme learning machine, the remora algorithm is introduced to optimize the randomly generated input weights and biases. In the optimization process, the root-mean-square error (RMSE) generated by the model is used as the fitness function for optimization, which significantly improves the generalization ability and robustness of the regularized extreme learning machine. In order to verify the effectiveness of the proposed algorithm in this paper, the color difference detection method is used to compare and analyze the images corrected by different models with the standard images. By comparing the chromatic aberration index of the corrected images, the performance of the algorithm in the illumination correction task can be evaluated. In conclusion, the proposed illumination correction model is based on remora optimized regularized extreme learning machine, and its effectiveness and superiority in the task of image correction under different illumination conditions are experimentally verified.

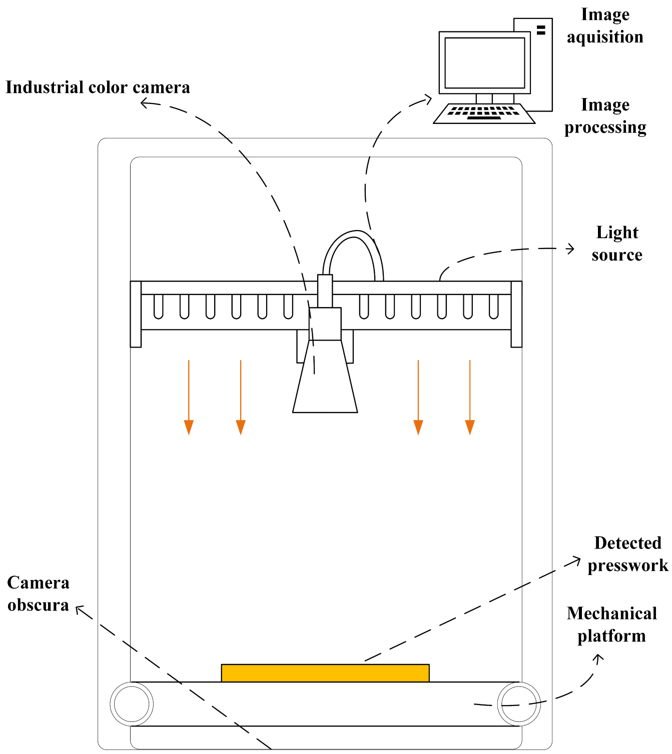


FIGURE 7. Diagram of experimental platform.

A. EXPERIMENTAL PLATFORM CONSTRUCTION

In the experiments, a total of 400 images of various types of printed matter were captured using industrial cameras under D65, D50, D55 and standard light sources, of which 360 were used as the training set and the remaining 40 as the test set. All images were captured in the experimental platform, as shown in Fig. 7.

B. EXPERIMENTAL SETTING

In order to verify the effectiveness of the algorithm proposed in this paper, the performance of the proposed ROA-RELM algorithm is compared with the ELM, KELM, RELM, SOA-RELM, WOA-RELM, BOA-RELM, BWO-RELM, PSO-RELM and SSA-RELM algorithms. The experiment is divided into two main steps: the first step puts the pre-processed experimental data into the model for training. The second step estimates the illumination information of the image through the model and then substitutes the output of the model into the Von Kries model to process the image to obtain the color of the restored image itself. During the experiments, all experiments were performed in (r, g) chromaticity space in order to reduce the impact of illumination variations on color analysis and processing and to reduce the amount of computation. Therefore, by obtaining the accurate light source information in the image and substituting it into the model for processing, the color of the image can be effectively corrected from unknown illumination to standard.

In this study, the image acquisition is taken with an industrial camera, and the algorithmic experiments are all done under the Windows 11 operating system and programmed in Pycharm using the Python language. The following is the information about the hardware and software configurations involved in the experiments: Hardware Configurations: Camera Model MV-CS050-10GC, Optical Lens FA12mm, Ring Light Source 24V RIF130110, Intel core i5 processor at 2.3GHZ, and 8GB of RAM. software configuration: python version 3.7, and development environment Pycharm 2019.1.4.

C. EXPERIMENT PARAMETERS

1) PARAMETER SELECTION FOR RELM

The main influencing factors of the RELM algorithm are the regularization parameter C and the number of hidden neurons L. The regularization parameter controls the complexity and fitting ability of the model; a larger regularization parameter reduces the risk of overfitting the model, but may increase the bias of the model. In contrast, smaller regularization parameters can improve the fit of the model, but may increase the risk of overfitting. A larger number of hidden neurons in the algorithm can increase the model's fitting ability, but may also increase the risk of overfitting and computational complexity, whereas a smaller number can lead to model underfitting. So, the fitting ability and robustness of the RELM model can be improved by experimentally choosing the appropriate regularization parameters and the number of hidden neurons.

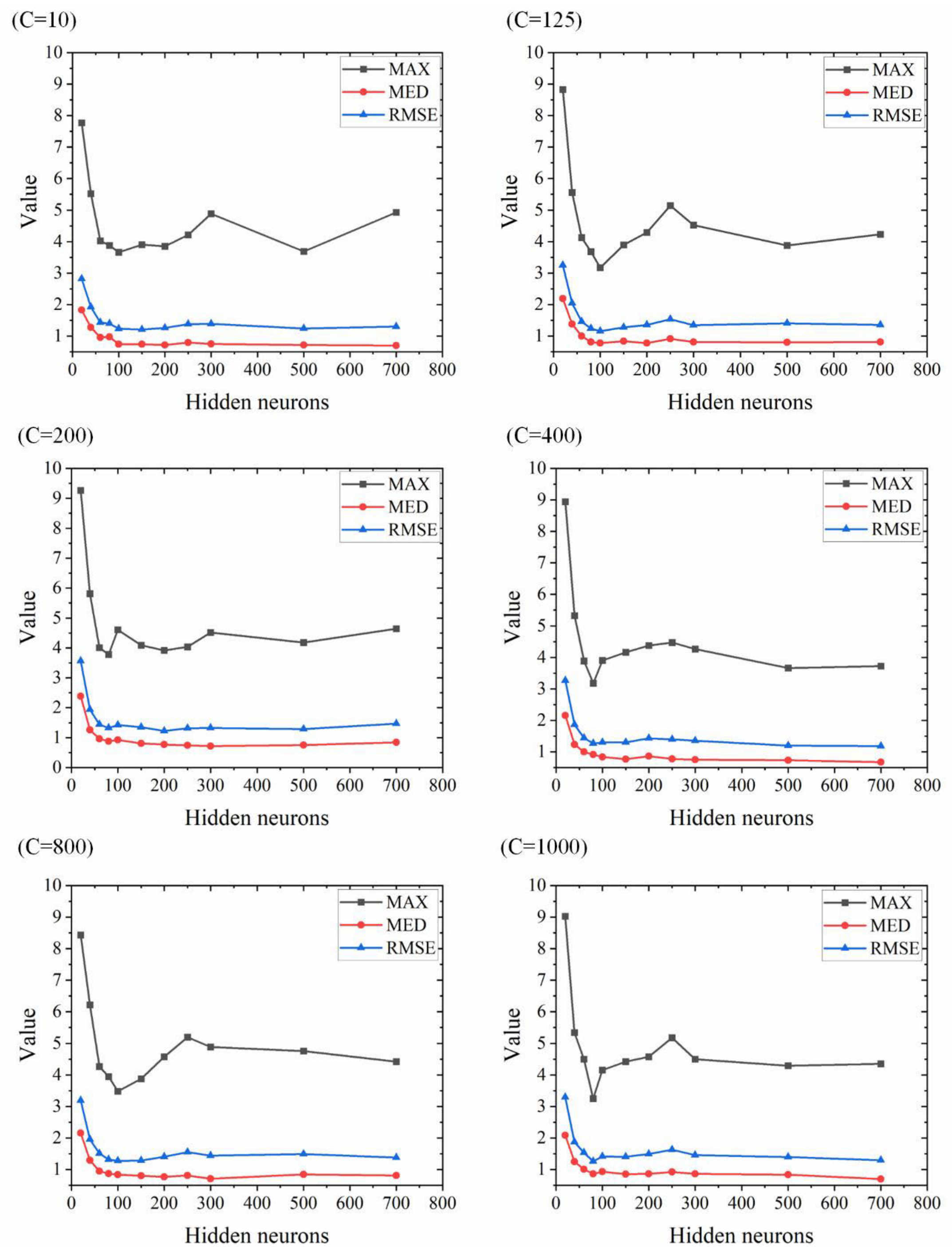


FIGURE 8. Regularization parameters and different parameter combinations of hidden neurons.

In this section, this paper conducts experiments for the regularization parameter C and the number of hidden neurons L. For the regularization parameter C, six values of 10, 125, 200, 400, 800 and 1000 are taken in this paper according to the references [28] and [29]. As for the number of hidden neurons, eleven values of 20, 40, 60, 80, 100, 150, 200, 250, 300, 500, 700 are taken in this paper, totaling 66 different parameter combinations. In order to get more reliable results, this paper conducts fifty experiments on different parameter combinations, taking the angle root mean square error (RMSE), the maximum angle error (MAX), and the median angle error (MED) as the evaluation indexes, and the smaller the value of the three proves that the algorithm error is smaller, and calculates the mean value of the fifty experiments. In order to more intuitively reflect the effects of regularization parameters and the number of hidden neurons

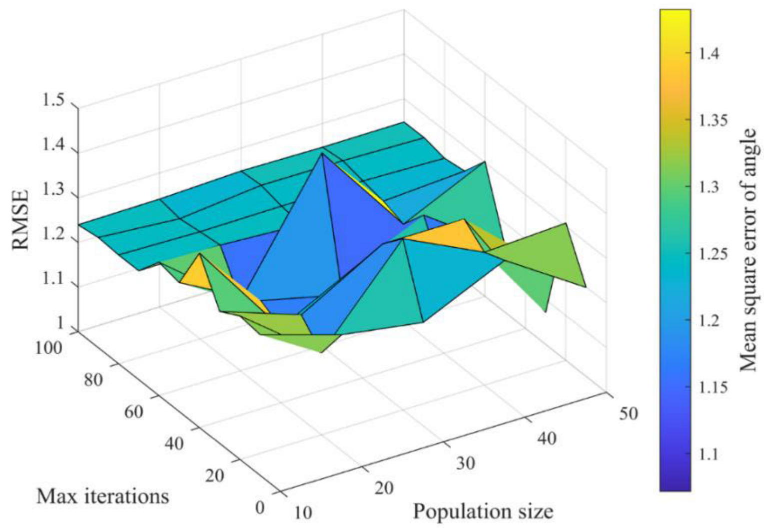


FIGURE 9. Effect of population size and number of iterations on angular root mean square error.

on the performance of the algorithm, the experimental results are plotted in this paper. Fig. 8 illustrates the experimental results of this paper. In the figure, the horizontal axis is the number of hidden neurons of the RELM algorithm and the vertical axis is the magnitude of the value.

By analyzing the experimental results, it can be observed that all three curves show a decreasing trend in the initial stage, and begin to rise after reaching an extreme point, and eventually level off. In the phase before the extreme point, all three curves trend downward in a straight line and the extreme point occurs around 100. This shows a gradual decrease in the error of the algorithm in the interval 0-100, with a larger decrease as the number of hidden neurons increases. In the phase after the extreme point, MED and RMSE change less, whereas MAX fluctuates more, but less relative to the previous phase. This suggests that when the number of hidden neurons is increased to a certain level, further increasing the number of hidden neurons has little overall effect on the error. Consider that an increase in the number of hidden neurons in the interval after 100 has little effect on the change in error and causes an increase in computational complexity and cost. The number of hidden neurons chosen in this paper is 100. For the choice of regularization parameters, this paper compares the errors generated under different combinations of parameters. The comparison reveals that the error is minimized when the regularization parameter is 125. Therefore, in this paper, the regularization parameter of 125 and the number of hidden neurons of 100 are chosen as the optimal parameter combinations for the RELM algorithm to be experimented.

2) PARAMETER SELECTION FOR ROA

In the ROA algorithm, the number of populations and the number of iterations are two key parameters, which have an important impact on the performance and convergence of the algorithm. The population size determines the scope and diversity of the search space of the algorithm, a larger population size can provide a wider search scope and avoid falling into local optimal solutions, but a larger population size will increase the computational complexity. Whereas the number of iterations determines the search depth and convergence of the algorithm, a larger number of iterations will provide more search opportunities and allow the algorithm to fully explore the solution space, but it will also increase the computational time of the algorithm. The number of populations and the number of iterations have an important impact on the performance and convergence of the ROA algorithm, and choosing the appropriate number of populations and the number of iterations is particularly important.

Reference [4], For the population size, five values of 10, 20, 30, 40 and 50 were chosen for this paper. As for the number of iterations, ten values of 10, 20, 30, 40, 50, 60, 70, 80, 90 and 100 are chosen in this paper. Both total fifty parameter combinations, and in this paper the angular root mean square error is used as the evaluation standard. Considering the existence of a certain degree of chance in the experimental results, this paper carried out each group of experiments fifty times, and took the average of the results of fifty experiments as the final results. Table 3 shows the angle root mean square error for different parameter combinations. In this paper, in order to more intuitively reflect the impact of the population size and the maximum number of iterations on the performance of the algorithm, the experimental results are plotted into a three-dimensional diagram, as shown in Fig. 9.

As can be seen from Table 3 and Fig 9, as the population size and the number of iterations change, the angle root mean square error is also changing and the magnitude of change is large, and the overall change interval is 1.0716～1.4325. When the number of populations is 10, the overall RMSE is

TABLE 3. Angle root mean square error for different parameter combinations.

	Population Size				
Max iterations	10	20	30	40	50
10	1.3152	1.2597	1.2317	1.3153	1.1990
20	1.3215	1.1833	1.3834	1.2976	1.3076
30	1.2957	1.2328	1.3361	1.3362	**1.0716**
40	1.3907	1.1684	1.2616	1.1668	1.1688
50	1.2889	1.1929	1.1505	1.2734	1.1476
60	1.2986	1.1569	1.4325	1.2173	1.3022
70	1.2438	1.2459	1.2362	1.2332	1.2451
80	1.2436	1.2400	1.2419	1.2426	1.2381
90	1.2469	1.2335	1.2528	1.2524	1.2482
100	1.2396	1.2417	1.2490	1.2468	1.2477

TABLE 4. Parameters settings for RELM optimization algorithm.

Algorithm	Parameter	Value
SOA-RELM	Number of populations	50
	Max_iteration	30
WOA-RELM	Number of populations	50
	Max_iteration	30
BOA-RELM	Number of populations	50
	Max_iteration	30
	P	0.8
	Power_exponent	0.1
	Sensory_modality	0.1
BWO-RELM	Number of populations	50
	Max_iteration	30
PSO-RELM	Number of populations	50
	Max_iteration	30
	C1	2
	C2	2
	w	0.8
SSA-RELM	Number of populations	50
	Max_iteration	30
	ST	0.6
	PD	0.7
	SD	0.2
ROA-RELM	Number of populations	50
	Max_iteration	30

around 1.3 regardless of the number of iterations, indicating that the number of populations is too small at this time, and the search space of the algorithm is not adequately covered, resulting in the algorithm not being able to adequately explore the search space, and thus falling into a local optimal solution. And when the population size is 50, the overall error is smaller and the mean value is 1.2, indicating that as the population size increases, the overall search space becomes larger and the error is gradually reduced. In terms of the number of iterations, the RMSE of the algorithm decreases to some extent as the number of iterations increases and then starts to level off. At the same time the increase in the number of iterations increases the risk of overfitting as well as the increase in computation time. In this paper,

TABLE 5. Angle errors of several algorithms on the set of printed matter images.

Measure	RMSE	MAX	MED
ELM	2.0923	8.9050	1.0748
KELM	1.8395	4.0962	1.3351
RELM	1.7751	6.0229	1.0726
SOA-RELM	1.3610	3.9764	0.9058
WOA-RELM	1.3871	4.0506	0.9135
BOA-RELM	1.2879	3.7745	0.8295
BWO-RELM	1.1464	3.1266	0.8025
PSO-RELM	1.2984	3.9989	0.8365
SSA-RELM	1.2057	3.5046	0.7738
ROA-RELM	1.1395	3.1503	0.7427

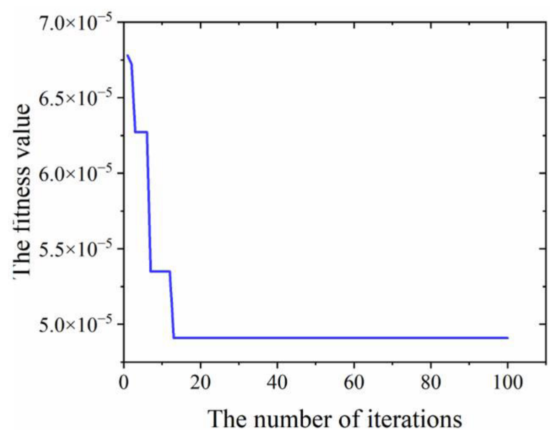


FIGURE 10. Variation curve of ROA optimized RELM parameters.

the parameter selection of the ROA algorithm is considered comprehensively and a population size of 50 and an iteration number of 30 are chosen as the optimal settings. The selection of the population size is a key issue; a smaller

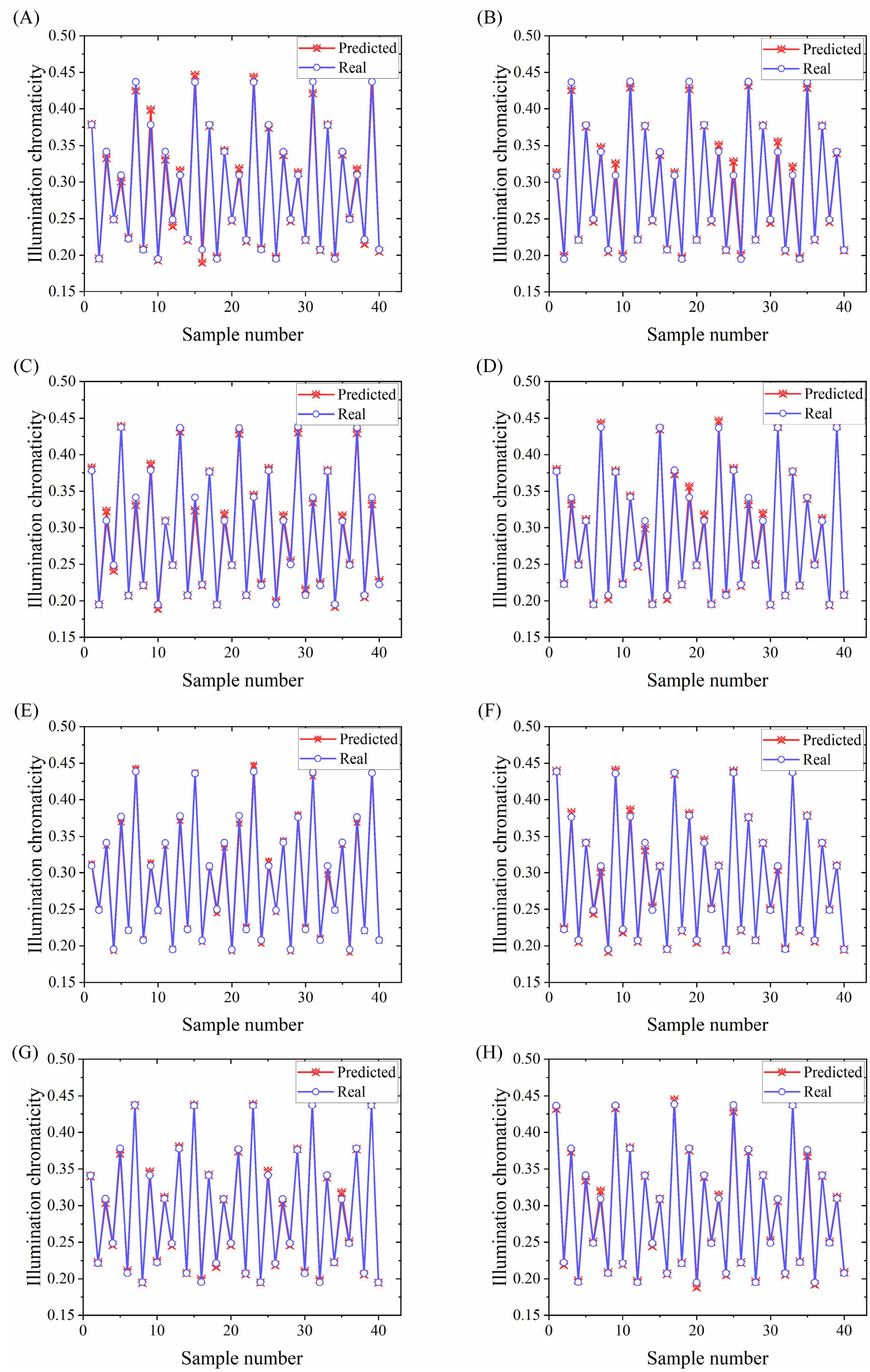


FIGURE 11. Prediction results of different models: A,ELM; B,KELM; C,RELM; D,SOA-RELM; E,WOA-RELM; F,BOA-RELM; G,BWO-RELM; H,PSO-RELM; I,SSA-RELM; J,ROA-RELM.

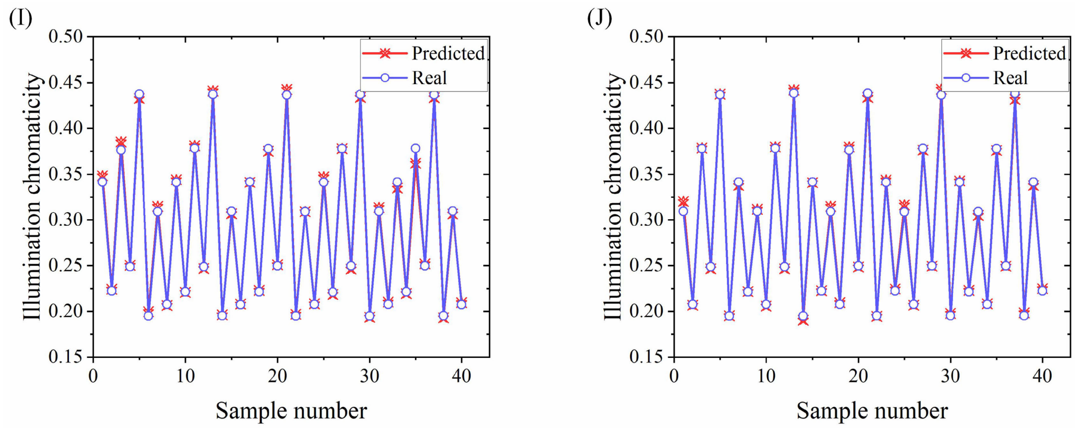


FIGURE 11. ***(Continued.)*** **Prediction results of different models: A,ELM; B,KELM; C,RELM; D,SOA-RELM; E,WOA-RELM; F,BOA-RELM; G,BWO-RELM; H,PSO-RELM; I,SSA-RELM; J,ROA-RELM.**

number may lead to a local optimal solution, while a larger number increases the computation time and resource consumption. In this paper, the population size is 50 to strike a balance between computational efficiency and search capability. The selection of the number of iterations also needs to be considered comprehensively, a smaller number of times may not be able to find the optimal solution, while a larger number increases the computational time and the risk of overfitting. In this paper, 30 iterations are chosen to balance the performance and efficiency of the algorithm. However, different problems and datasets may require different iterations. The stability and robustness of parameter selection also need to be noted, and small changes may affect the algorithm performance. Therefore, parameter selection should be further explored on a case-by-case basis, and a parameter strategy suitable for a particular application should be developed by balancing problem complexity, resource availability, and algorithm performance.

3) EXPERIMENTAL PARAMETERS OF THE RELM OPTIMIZATION ALGORITHM

In order to verify the performance and effectiveness of the ROA-RELM algorithm proposed in this paper, this paper compares it with the ELM, KELM, SOA-RELM and WOA-RELM algorithms. In ELM, the number of hidden neurons was set to 100 and the Sigmoid function was used as the activation function. And in KELM, the kernel function is chosen to be RBF. In order to ensure the fairness of the experiment, this paper sets the population size of the relevant optimization algorithm to 50, the maximum number of iterations to 30, and limits the search space boundary to [−1,1] and the relevant algorithm parameters are shown in Table 4.

D. EXPERIMENTAL RESULTS AND ANALYSIS

In this section, in order to verify the effectiveness of the algorithm proposed in this paper, ROA-RELM is compared with other illumination correction models. In order to avoid the chance of experimental results, all experiments were repeated fifty times and the mean value was taken as the final experimental result. The experimental angular root mean square error (RMSE), maximum angular error (MAX), and median angular error (MED) are used as evaluation metrics to evaluate the performance of the illumination correction algorithm. The experimental results are shown in Table 5.

In constructing the ROA-RELM illumination correction model, this paper adopts the ROA algorithm to optimize the weights and biases of RELM, and refer to "(21)," is used as the fitness function, and Fig. 10 demonstrates the change curve of the fitness when using ROA to find the optimization. From the figure, it can be seen that as the number of iterations of the population increases, the degree of adaptation is decreasing. When the number of iterations reaches 13, the degree of adaptation stabilizes.

In Table 5, it can be clearly seen that in the metric of RMSE, the proposed algorithm in this paper performs the best, reaching 1.1395. Compared to ELM and RELM the error is smaller, whereas the other algorithms have an RMSE in the range of 1.2-1.3, proving that the algorithm has a smaller overall error compared to the other algorithms. In this indicator of MAX, BWO-RELM has the lowest value, which indicates that the maximum error of BWO-RELM is small and does not produce large errors, and the algorithm proposed in this paper does not differ much from the value of BWO-RELM. And among the MED metrics, the algorithm proposed in this paper is the minimum. In the three evaluation indexes, ROA-RELM performs better than the other algorithms, and the algorithm is more stable and produces less error, which once again proves the superiority of the ROA-RELM algorithm.

Fig. 11 shows the predicted results versus the true values for printed matter tested on different illumination correction models, where the horizontal coordinate represents the number of samples in the sample test set, and the vertical coordinate represents the illumination chromaticity of the print test set.

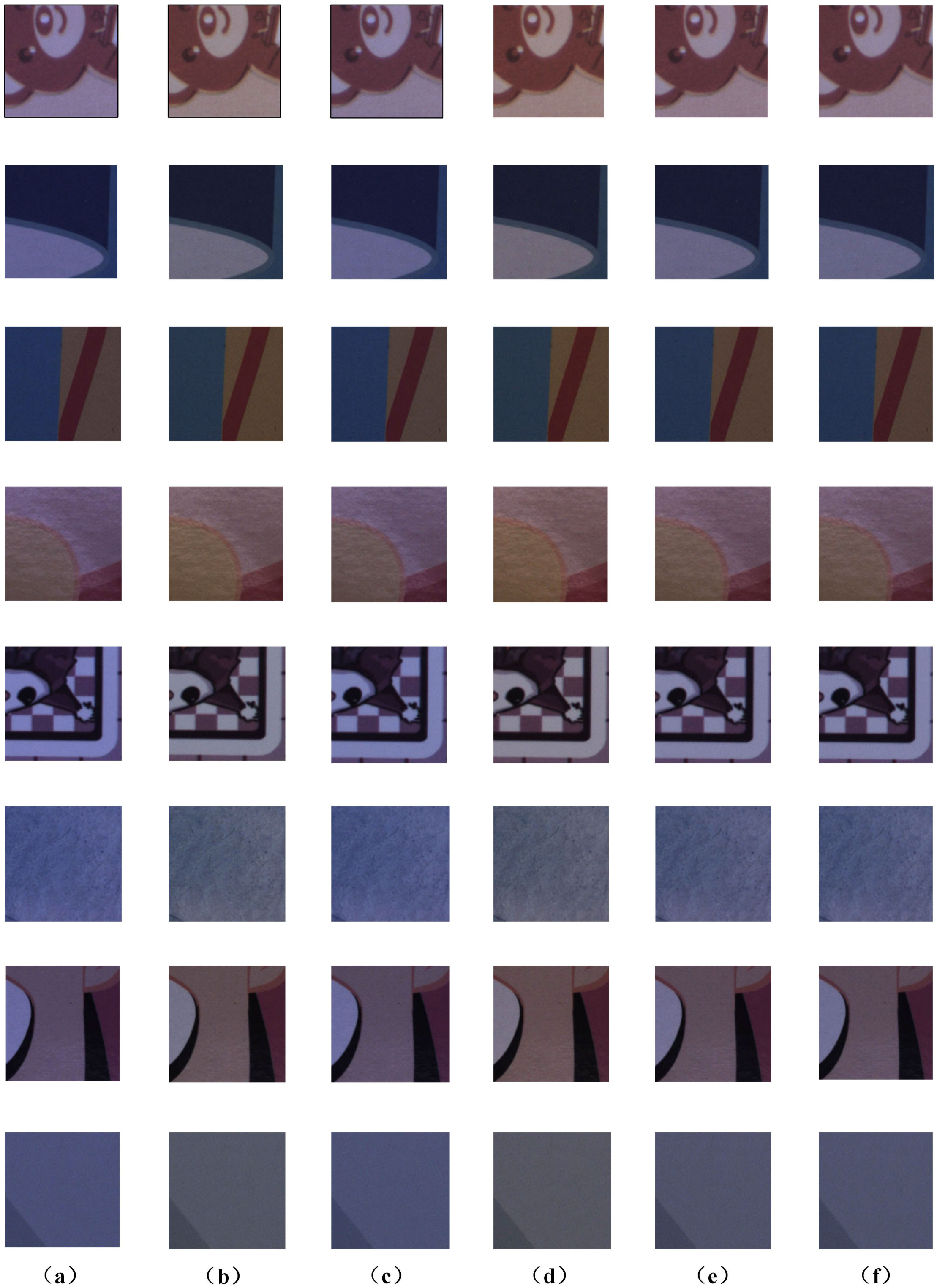


FIGURE 12. Illumination correction results of different algorithms on printed matter images:(a) Standard image (b) Uncorrected image (c) Method proposed in this paper (d) ELM-based color constant (e) RELM-based color constant (f) PSO-RELM-based color constant.

In Fig. 11 and Table 5, it is clear that ELM has the largest error in illumination chromaticity compared to the other algorithms, whereas KELM and RELM have reduced errors compared to ELM, but the reduction is small. The use of intelligent optimization algorithms to optimize the RELM is more obvious in reducing the illumination chromaticity

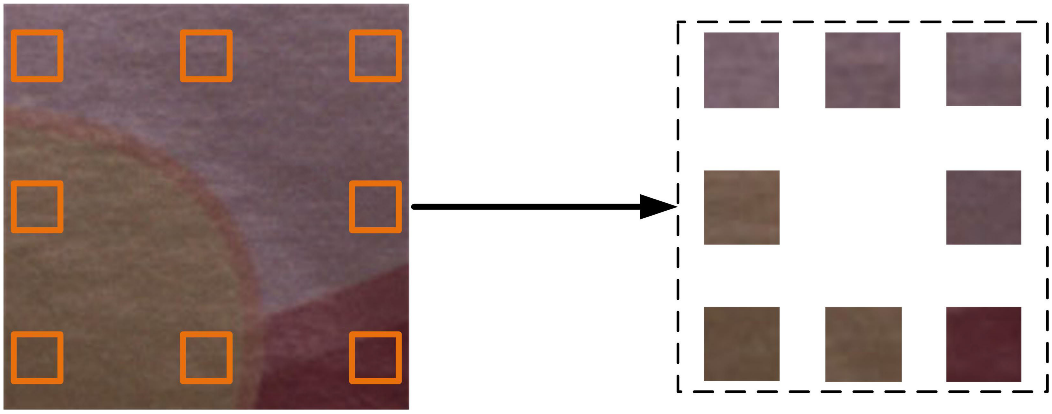


FIGURE 13. Schematic diagram of picking point.

error, among which ROA-RELM and BWO-RELM are the most effective, and ROA-RELM has the highest prediction accuracy. Algorithmically optimized RELM show a substantial improvement in algorithmic performance compared to non-optimized RELM. Compared to other algorithms used to optimize the RELM model, the ROA-RELM model reduced the angular error by 11.04%. The experimental results show that ROA-RELM has high prediction accuracy, produces small errors, and can achieve better illumination correction.

E. APPLICATIONS

In order to verify the effectiveness of the algorithm proposed in this paper in practical applications, the output of the model is brought into the Von Kries model for processing, and the image after illumination correction is obtained and compared with the standard image.

TABLE 6. Chromatic deviation between different model corrected images and standard image.

	ΔE	ΔV	ΔS	ΔH	ΔL	Δa	Δb
ELM	4.85	19.65	27.84	-1.32	0.38	-5.20	10.28
KELM	2.78	-6.73	-17.8	0.28	-0.86	3.67	-6.50
RELM	2.34	11.15	9.61	-0.36	-0.11	-2.47	4.43
SOA-RELM	1.62	-2.03	-11.8	0.08	-0.04	1.90	-3.75
WOA-RELM	1.76	9.65	6.70	-0.45	-0.05	-2.05	3.43
BOA-RELM	1.29	-0.54	-9.93	-0.01	-0.17	1.38	-2.85
BWO-RELM	1.22	6.67	1.27	-0.37	0.24	-1.00	1.36
PSO-RELM	1.68	9.72	7.21	-0.28	0.54	-2.10	3.54
SSA-RELM	1.11	5.68	-0.61	-0.51	0.03	-1.03	1.17
ROA-RELM	1.09	3.18	-4.43	-0.21	-0.43	0.10	-0.57

In this paper, several images after the restoration of different models are shown in Fig. 12, and a group of these images are selected to be taken by taking points as shown in Fig. 13, and then the CIEDE2000 chromatic deviation detection formula is used to calculate the chromatic deviation between the images corrected by different models and the standard images and compare them with each other, and the experimental results are shown in Table 6. By analyzing Fig. 12 and Table 6, it is clear that the ROA-RELM model gives the best restoration of the image to be corrected and the image is close to the color of the standard image. ELM has a poor illumination correction effect on the image and the corrected image is not much different from the uncalibrated image, whereas the algorithms BOA-RELM, BWO-RELM and SSA-RELM have a slightly lower correction effect than the algorithms proposed in this paper, although their illumination correction effect is stronger than that of ELM and RELM. Compared to other algorithms used to optimize the RELM model, the color difference detection accuracy of the ROA-RELM method is improved by 24.22%. The experimental results prove that the method proposed in this paper has higher prediction accuracy compared to other methods.

V. CONCLUSION

In order to solve the problem of large color differences caused by illumination during quality inspection of printed matter, this paper proposes a regularized extreme learning machine based on remora optimization algorithm for printed matter illumination correction model. First, the chromaticity features of the printing image are extracted as input vectors based on the grey edge. The remora algorithm is then used to optimize the weights and biases of the regularized extreme learning machine, which improves the accuracy and convergence speed of the model. Finally the images are corrected for illumination using the ROA-RELM model with optimal parameter combination. In order to verify the effectiveness of the proposed algorithm, this paper conducts a number of experiments on the same dataset using different algorithms. The experimental results show that the algorithm proposed in this paper has good performance and competitiveness compared to other algorithms. This paper also analyzes the images before and after correction by using chromatic deviation detection, and the results show that the algorithm proposed in this paper has the best recovery effect on the images.

Although the illumination correction algorithm proposed in this paper has reduced the effect of illumination changes to a certain extent, there is still room for further optimization. Optimization from various aspects, such as faster training time, higher accuracy, more complex application scenarios, etc., requires further optimization and enhancement of the algorithm, including finer parameter tuning, stronger adaptability to illumination variations, and the ability to cope with the joint correction of multiple light sources. In the future, our research work will expand the application areas of the algorithm, not only for plastic flexible packaging, but also for more types of printed matter, such as foil stamping process printed matter, hard box packaging. Illumination correction is only one part of printed matter quality inspection, and we plan to combine it with other image processing and machine learning techniques, such as feature extraction, image segmentation, etc., in order to achieve more comprehensive and efficient printed matter quality inspection.

Although the illumination correction algorithm proposed in this paper has achieved good results in printed matter quality detection, we need to consider the ethical issues of the related technology in the process of application and promotion. With the development of technology, we need to ensure that the algorithms and models used do not violate personal privacy and data security. In the process of detecting the quality of printed matters, production-sensitive data of producers may be involved. Therefore, during the implementation process, users should take appropriate privacy protection measures to ensure data security and legitimacy, and comply with relevant legal and ethical guidelines. The application of the algorithms proposed in this paper aims to restore the accuracy and consistency of printed matter color. The use and application of the algorithms should follow appropriate ethical and legal guidelines to ensure that the algorithms are not misused or used for inappropriate purposes.

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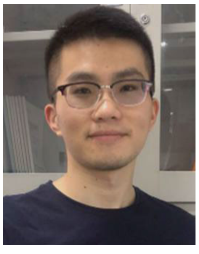

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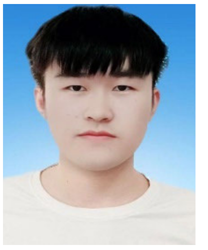

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