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Automatic Coloring Algorithm for Hand-Drawn Illustrations Based on Human Vision Model

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Abstract

Objectives: The objective was to develop an advanced, developed-up-to-date method that utilizes visual nonlinearity, contrast sensitivity, and brightness adaptation to colorize human-drawn pictures by itself taking into account human color perception. To minimize the damaging effect of computational findings on the human vision system and also to enhance the visual quality and color accuracy of digital pictures by identifying commonalities among the possible solutions. **Methods:** This research makes use of visual traits like contrast sensitivity, visual nonlinearity, and brightness adaptation in conjunction with an optimization method for pattern searches. The proposed algorithm is tested and fine-tuned using the xRite Color Checker 24-color card. Mathematical modeling and actual trials compare the model's algorithm performance to that of more conventional approaches like least squares and limited least squares, with the goal of reducing the inaccuracy in color differences. **Findings:** The studies' best outcome was a mean of 3.25, a standard deviation of 0.72, a maximum of 6.75, and a low of 0.42. Additionally, less than three percent of the corrected color blocks had a color difference of more than forty-one percent. These outcomes highlight the algorithm's capacity to produce visually accurate images by simulating human visual perception. **Novelty:** This study introduces a novel method for a color correcting system that takes into account features of the human visual system. Visual multichannel processing and nonlinearity are two of its defining characteristics that allow it to make incredibly realistic graphics and packaging designs by bridging the gap between machine-generated results and actual human perception.

Keywords: Graphic design; Image coding; Colorization; Human vision; Pattern Search Algorithm

1 Introduction

Having well-designed packaging is a crucial part of developing a product. Selecting the suitable wrapping resources, graphic design, and corresponding with inventive workmanship improves the product's overall appearance by taking the product's purpose, form, and material into account[(1)]. In addition to the items' functional qualities, package design may be seen as another way to increase the affinity between products and customers. A product's value, reputation, and ability to stand out from the competition may all be greatly improved with well-designed packaging. Presently, most studies are focusing on computer-assisted three-dimensional modelling of package design[(2)]. A more scientific approach to package design is possible using three-dimensional modelling as opposed to visual design. However, low picture quality is an issue with the current research's 3D modelling design of the package structure[(3)]. Research on colour correction and highlight removal based on human visual characteristics is proposed for colour and illumination uniformity. Machine vision systems need to undergo transformations to create an end product that is nearly identical to what the human eye would see in order to mimic human color vision perception[(4)]. The upgraded pictures are optimized for computer processing, have greater visual effects, and are more in accordance with human eye characteristics thanks to algorithms[(5)],[(6)].

Automatic coloring, color matching, and picture processing have all come a long way, but there are still some unanswered questions. Existing algorithms, such those based on deep learning and artificial intelligence, tend to put an emphasis on accuracy and performance at the expense of human creativity and subjective visual perception, both of which are essential for cultural and artistic applications[(7)]. While current colorization methods are effective, they pay little attention to the unique needs of hand-drawn graphics in favor of generalized grayscale-to-color conversions or cultural commodities[(8)]. Concerning inconsistencies brought on by inaccurate color matching in intricate designs, the majority of methods, even VR-based solutions, fall short. Furthermore, these methodologies still have challenges when it comes to computational efficiency, especially in real-time applications[(9)]. To improve realism while keeping computing efficiency, it is necessary to include human visual models into algorithms. This is where a significant gap exists. By filling these gaps, between the demands of creative and visual design professionals and the outputs produced by machines[(10)].

The primary work is to improve digital artwork and graphic design workflows, especially for drawings that are hand-drawn. Animated films, comic books, and digital content designers all benefit greatly from it because of the importance of realistic and visually beautiful colorization in these fields. Also, it's useful for packaging design because it will fix colors accurately for both digital and physical product visualization. The algorithm is also helpful for digital archiving and cultural preservation when it comes to restoring and colorizing faded or grayscale photos. To reduce the gap between computational processing and creative expression, it incorporates features of human vision, guaranteeing results that are in close agreement with human perception.

2 Methodology

2.1 Models and Features of Human Vision

The eye is the primary sensory organ for taking in its immediate surroundings. The eye to transmission along the visual route to processing by the visual sensory and perception centre, the information travels the length of the visual axis. One of them is visual perception, which works in parallel with the brain, rather than serially. As a whole, the visual process begins with the reception of light stimuli by the human retina and continues with their processing by the retina's cone cells, which in turn provide information that the brain uses to respond. The information reaches the visual channel after being processed simultaneously by the balanced right and left eyes. Prior to generating the final output for its feature extraction, decision-making judgement, etc., the cerebral cortex will store the picture data. Variability in light, visual attributes between channels, nonlinearity of visual processing, contrast sensitivity, and masking effects are a few of the hypothesized human visual system properties that are grounded on the visual system's physiological organization as demonstrated in Figure 1.

2.2 Human Vision-Based Color Correction

The human eye's highly developed ability to perceive color allows it to identify and interpret things' colors in a wide range of lighting conditions. If you light a white item with a low-temperature source, it will seem red, but if you light the same thing with a high-temperature source, it will look blue. However, colour constancy allows us to see objects as white even when their actual colours are different. Contrary to what was said before, machine imaging systems cannot automatically adjust to different light sources. Machine vision systems need to undergo transformations to create an end product that is nearly identical to what the human eye would see in order to mimic human color vision perception. The process of achieving this effect is known as white balancing, and it makes use of a color-adaptive transformation as shown Figure 2.

Fig 1. The pattern search optimization algorithm-based colour correction method's flowchart

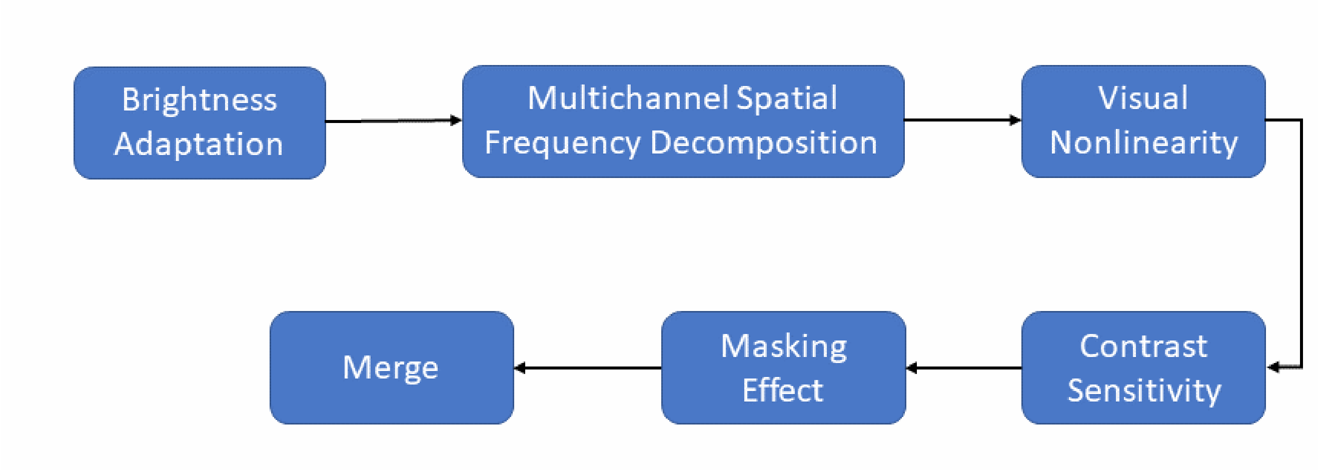

Fig 2. A Basic Vision System Model

The beginning value influences the correction outcome of a pattern search optimization-based colour correction method, which finds a local optimum. Therefore, the color correction technique is considered for the visual properties of the human eye through simulation of the way the eye perceives colors. In our method, we maintain the same numerical values obtained in the environment and take away the white point hue value from the pixel hue value in every original image. The following formula may be used to represent the equation given above:

$$f_{Iconrrectd} = f_1 \theta f_{WF}.$$

The subtraction operation θ, which may be thought of as a colour filter.

2.3 Factors Influencing Colour Aberration

Uneven spatial brightness distribution and colour deviation are two common complaints about 3D-printed packaging compared to the actual thing. The subsequent image processing, including feature extraction, categorization, and so on, will be impacted by the color's authenticity to some degree[11]. Consequently, the actual, human-eye-approaching picture, the rationale behind the obtained image's colour distortion and how to rectify it. 3D design software uses the same imaging paradigm as a conventional camera, which uses reflected light to create an image on the focus plane, in terms of the optical image imaging concept[12],[13]. In real imaging, however, everything will seem different due to the unique photosensitive media as shown in Figure 3. The image quality is also impacted, and the acquired industrial image will have colors that differ from what our eyes perceive in reality. This is due to the fact that some of the sensors in the camera use CMOS and others use CCD, which leads to different sensing characteristics, optical lens characteristics, relative aperture, field angle, and focal length, as well as different chromaticity characteristics of the light source[14].

2.4 Traditional Color Correction Techniques

2.4.1. Polynomial Regression-Based Color Correction

Polynomial regression analysis, the most widely used method in statistics, has solved many practical problems, large and small. Through continuous observation, experiment, test, and summary, regression analysis can find out the interdependence of different variables. Regression analysis is generally divided into nonlinear and linear[15]. This study adopts the form of linear regression, and the mathematical model can be expressed as

$$|Y| = X\beta + Z,$$

Z is the random value, X is the independent variable, β is the linear regression parameter, β is the standard value of the colour card standard target of the observation object, the size is of order $N \times P$, and β is defined as a vector of real numbers from 1 to

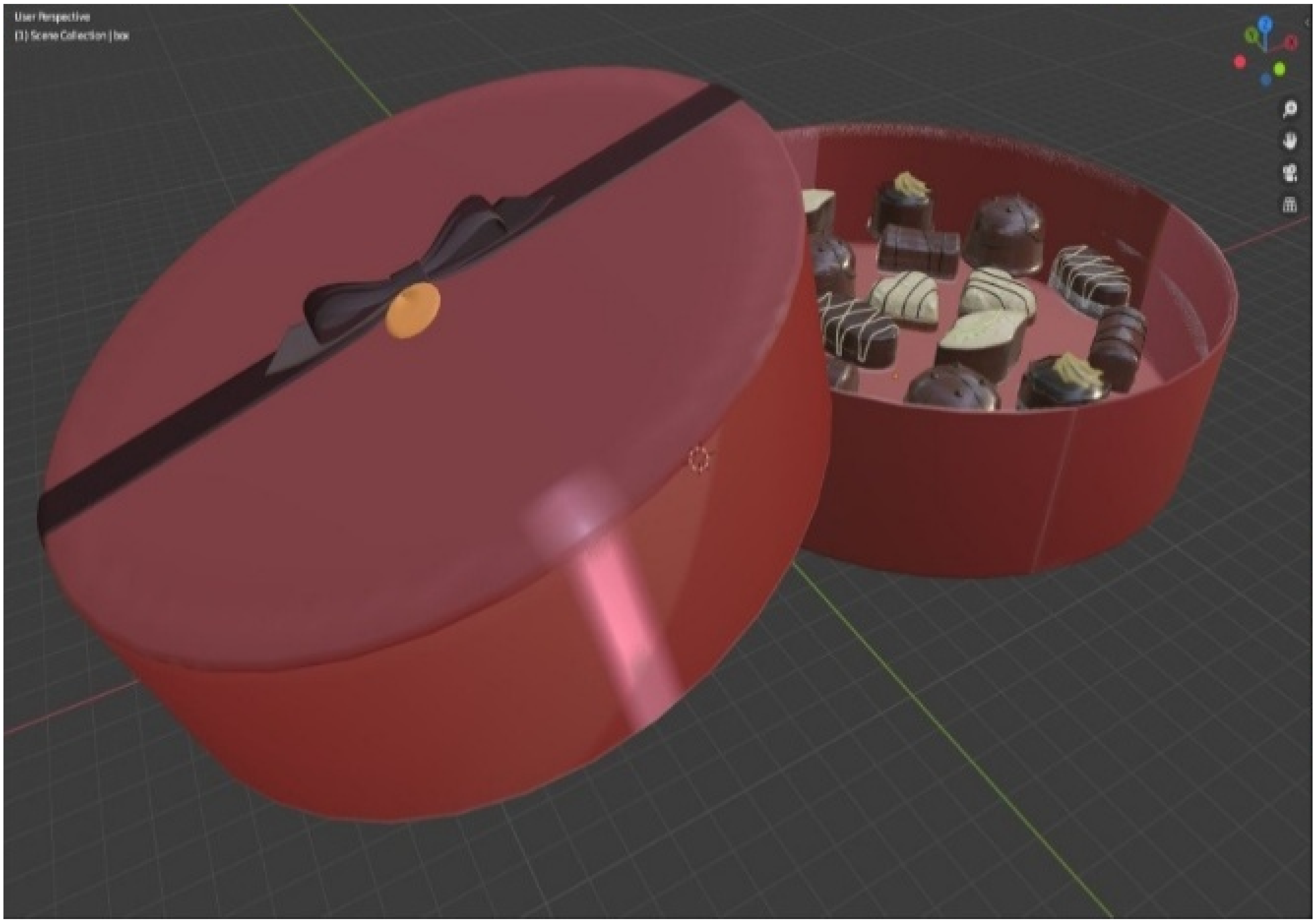

Fig 3. The inner packing container design in three dimension

p. Among them,

$$\begin{bmatrix} x_{11} & x_{12}x_{13}\cdots & x_{1P} \\ x_{21} & x_{22}x_{23}\cdots & x_{2P} \\ \cdots & \cdots\cdots & \cdots \\ x_{N1} & x_{N2}x_{N3} & x_{NP} \end{bmatrix}$$

It is presumed that, because the predicted value of the random disturbance vector Z may be entered into the mathematical model XH,

$$E(Z) = 0.$$

It is equivalent to

$$E[Y] = X\beta.$$

Keep in mind that when a parameter is derived in a linear regression model, the derivative is no longer related to the parameter. The value of the standard colour card—the regression model's vector Y—before the linear regression model to fix the colour. The following formula should be satisfied by the necessary value β:

$$\min \|Y - \beta X\|$$

The second-order norm is represented by $\|\bullet\|$, and the parameter matrix used for this investigation is the solution γ produced using the least square approach. To demonstrate how to generate the model parameters, the first step is to use the 3×3 matrix as a reference.

$$\begin{bmatrix} X_1 & Y_1 & Z_1 \\ X_2 & Y_2 & Z_2 \\ \cdots & \cdots & \cdots \\ X_N & Y_N & Z_N \end{bmatrix} = \begin{bmatrix} R_1 & G_1 & B_1 \\ R_2 & G_2 & B_2 \\ \cdots & \cdots & \cdots \\ R_N & G_N & B_N \end{bmatrix}^T \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix}$$

where the parameters satisfy

$$X = \begin{bmatrix} R_1 & G_1 & B_1 \\ R_2 & G_2 & B_2 \\ R_3 & G_3 & B_3 \end{bmatrix}^T$$

$$Y = \begin{bmatrix} X_1 \\ X_2 \\ X_3 \end{bmatrix}$$

$$\beta = a_{11} a_{21} a_{31}^T$$

As an example, let's look at the first column of the model coefficient matrix $\beta 1$.

$$Y = X\beta_1.$$

The product of the aforementioned formula and the result $\beta 1$ should match the given equation.

$$X^T Y = X^T X \beta_{1,}$$

$$\beta_1 = \left(X^T X\right)^{-1} X^T Y$$

Other columns of the model's coefficient matrix may also have their values solved in a similar fashion. The following is a synopsis of the standard method of colour correcting based on the preceding introduction:

- You need make the colour card standard goal for the trial. If you want your experimental findings to be accurate, you should choose a standard target that covers as many colour gamut's as feasible.
- In order to analyze the colour card, use the formula above to get its particular chromaticity value, or Y. The xRite Color Checker 24-color card is used as the standard value in this article.
- Find the RGB value that needs fixing.
- Through the use of polynomial regression, the model parameter matrix H is derived.

2.4.2. Constrained Least Squares Color Correction

One of the most important factors in successful colour correction is the exact reproduction of the white block. While the least squares technique can get all the colours as near as feasible, it can't promise that the white block area will stay white after correction. As a result, the requirement that the white block stays the same both before and after correction is added to this research.

The set of corrected XYZ values is represented by X [x, y, z] in the least squares approach, which is a $q \times 3$ matrix. The set of raw RGB values that need to be rectified is X [x, y, z], which is also a $q \times 3$ matrix. The following is an example of how to minimize a linear map using the residual sum of squares:

$$F = \left\|\overline{X} - X \;\; M\right\|_2^2$$

A 3×3 matrix called M has to be solved, and the previous formula is the same as minimizing the residual, as shown below:

$$\varepsilon^2 = \sum_{i=0}^{3} \left[\overline{X}^{(i)} - \sum_{k=1}^{3} m_i, kX^{(k)}\right]^2$$

The following formula should be minimized if a column element with a linear parameter M is required:

$$\frac{\partial \varepsilon^2}{\partial m_{i,k}} = 0, k = 1,2,3$$

So, to summarize the linear parameter matrix M,

$$\begin{bmatrix} \sum_{i=1}^{q} \left(x_i^{(1)}\right)^2 & \sum_{i=1}^{q} x_i^{(1)} x_i^{(2)} & \sum_{i=1}^{q} x_i^{(1)} x_i^{(3)} \\ \sum_{i=1}^{q} x_i^{(2)} x_i^{(1)} & \sum_{i=1}^{q} \left(x_i^{(2)}\right)^2 & \sum_{i=1}^{q} x_i^{(2)} x_i^{(3)} \\ \sum_{i=1}^{q} x_i^{(3)} x_i^{(1)} & \sum_{i=1}^{q} x_i^{(3)} x_i^{(2)} & \sum_{i=1}^{q} \left(x_i^{(3)}\right)^2 \end{bmatrix} \begin{matrix} m_{1,k} \\ m_{2,k} \\ m_{3,k} \end{matrix}$$

$$= \begin{bmatrix} \sum_{i=0}^{q} x_i^{(1)} \overline{x}_i^{(k)} \\ \sum_{i=0}^{q} x_i^{(2)} \overline{x}_i^{(k)} \\ \sum_{i=0}^{q} x_i^{(3)} \overline{x}_i^{(k)} \end{bmatrix}$$

You may make the previous formula shorter by rewriting it as: In this case, B represents

$$B = X^T X, X = \begin{bmatrix} X_1^{(1)} & X_1^{(2)} & X_1^{(3)} \\ \ldots & \ldots & \ldots \\ X_q^{(1)} & X_q^{(2)} & X_q^{(3)} \end{bmatrix}$$

the value of d may be written as

$$d = X^T \overline{X, X} = \begin{bmatrix} \overline{X}_1^{(1)} & \overline{X}_1^{(2)} & \overline{X}_1^{(3)} \\ \ldots & \ldots & \ldots \\ \overline{X}_q^{(1)} & \overline{X}_q^{(2)} & \overline{X}_q^{(3)} \end{bmatrix}$$

Hence, the following is the necessary linear parameter matrix M for this study:

$$M = \left(X^T X\right)^{-1} X^T \overline{X}.$$

Unfortunately, the noise cannot be removed using the conventional least square approach, leading to erroneous correction and the white block portion that has been corrected cannot stay white. The exact replication of white blocks is the fundamental concern for the effectiveness of colour restoration. As a result, the requirement that the white block stays the same both before and after correction is added. X stands for the collection of corrected XYZ values in the restricted least squares approach. X stands for the original RGB values that need fixing. Points indicate the original white block's RGB value in the constraint term, whereas x^C represents the XYZ value after correction of the associated colour block. As seen in the following equation, the limited white area is made accurate by adding the Lagrange multiplier:

$$F = \left\|\overline{X} - X \;\; M\right\|_2^2 + \mu \sum_{K=1}^{3} \left(\overline{x}_k^C - \sum_{j=1}^{3} x_j^C m_{jk} \right)$$

The Lagrange multiplier, denoted by μ, guarantees an exact correction of the confined white area $\overline{x}^C$ to x^C. Concurrently, the following equation has to be satisfied:

$$\left\| \left(\overline{x}^C\right)^T - \left(X^C\right)^T M \right\| = 0$$

Determine the Purposeful Action. Establishing the specified goal function follows the determination of the corrective model. An in-depth analysis of human visual features has led to the proposal of a pattern search-based colour correcting approach. The new approach matches the human eye's colour perception more closely than the old classical method of colour correcting.

$$[X, Y, Z] = \left[(B - \tau_b), \left(G - \tau_g\right), (R - \tau_r)\right] M$$

Having determined that the matrices P and Q on each side of the equation are necessary for solving the linear regression parameter matrix M, the analysis as described above. Hence, the objective function is defined in this research as matrix Q, where Q is a $q \times 3$ matrix representing the standard XYZ value and is also the corrected XYZ value's matrix. In the end, this research builds a 3×3 linear parameter matrix M that minimizes both the standard and corrected XYZ values. Reducing the difference between the two pictures to make the difference in XYZ values as little as feasible would ensure that the image corrected by the linear parameter matrix is most in accordance with human visual perception, in terms of the overall visual perception difference. It follows that the average value of the colour difference between the corrected and standard XYZ values should be used as an optimization item when building the objective function.

2.4.3. Pattern Search

It is common practice to use a standard illuminate, such a D65 light source, to determine the standard value of the colour card of the standard sample using adaptive brightness adjustment. Nevertheless, elements including light sources, cameras, image sensors, and lenses will impact industrial cameras when they take pictures[16]. This will cause variations in brightness and colour in the original, captured photographs. Differences between the original RGB value and the corrected RGB value may cause phenomena like colour shift and brightness differences[17],[18]. To achieve a more precise picture and make sure the brightness of the corrected image is the same as the original, this research adds the brightness adjustment parameter λ to affect the sample's standard colour card value; by default, λ is set to 1. Now, the matrix Q that represents the typical XYZ values is renamed to Q $[\lambda_X, \lambda_Y, \lambda_Z]$. To get the corrected sample colour value, fix the original RGB value using the correction matrix M, and then solve the linear regression parameter M using the pattern search method[19].

This should be done before calculating the linear parameter matrix M. Right now, you have to decide whether the brightness limitation requirements are satisfied. In such case, you'll need to tweak the brightness adjustment parameter Λ and recalculate the correction matrix M until the change in brightness falls within the acceptable range. It is common practice to set the brightness restriction to white block brightness.

$$|Y_t - Y_m| < \epsilon$$

ε stands for the maximum permitted brightness adaptation range, Yt is the corrected brightness of the white patch in the CIEXYZ colour space, Ym is the original brightness of the white patch in the CIEXYZ colour space. This approach sets the ε value to 5 based on the human eye's sensitivity to brightness in its visual characteristics, and the final solution to the linear parameter matrix M must meet this requirement.

2.4.4. Pattern Search Algorithm

The optimizing for a problem with N independent variables, pattern search approaches are often used. Optimization issues involving non-derivable functions or functions that are very difficult to derive may be effectively solved using this method as it does not include the objective function's derivative in the computation[20],[21]. Finding the independent variables X0, X1, X2, etc. is the first step of the pattern search technique. As these variables approach the ideal point, the search will continue until it encounters the termination condition.

Here is the detailed procedure: first, randomly assign each element of the matrix M a starting value (xi), which is usually the unit matrix. Then, the objective function value f(Xi) when M is the initial value. The objective function value $f(Xi + V(j) \prod L)$ at this time, where $j \in (1, 2, ..., 2N)$, is then calculated by increasing or decreasing the value of the independent variable. After updating the independent variable to $Xi + 1Xi + V(j) \prod L$, the search is considered successful. If the new objective function value is better than the old one, the search centre may be changed, and the step size can be raised or lowered for the next search. If the new objective function value is not optimum, use Xi + 1 as the search centre and $LL \prod \delta$ as the step size (where $\delta > 1$ indicates to raise the step size to expand the search range). The search is considered unsuccessful if the value of the prior goal function is surpassed. Keep using the previous Xi as the centre and lower the search step size by setting the step size as $LL \prod \lambda$ (where $\lambda < 1$ indicates to lower the search step size to narrow the search range). Repeat this process until you reach the cut-off condition, which is typically set when the number of iterations reaches a specified value. The whole process of the colour correction approach that is based on the pattern search optimization algorithm[22],[23].

3 Results and Discussion

The experimental item was the xRite Color Check 24-color colour card. When doing quantitative analysis, the standard method for determining distance is the geometric mean. A more effective correction is achieved when the discrepancy is less. This study's real-world implementation begins with obtaining the correction matrix M from the 24-color blocks, followed by obtaining the target picture in the same setting and by using the correction matrix, the rectified picture. Various methods are used to process the same colour card picture, and the experimental outcomes are displayed. See Figure 4 for the original colour chart, Figure 4 for the results of the least squares method-based colour correction, Figure 4 for the results of the least squares method-based colour correction with constraints, Figure 4 for the results of the pattern search optimization algorithm-based colour correction, and Figure 4 for the results of the human eye-based colour correction. Using the white block in the bottom left corner as an example, it is clear that the original image's white block was blue. In terms of colour correction, the least square approach and the restricted least square method produced the lowest results. The pattern-based search effect is considerably better than the previous two, and while the blue of the white block has been fixed, there is a major colour deviation of other colour blocks, such as the blue block in the top right corner, which makes the whole image blue. Figure 4, on the other hand, shows a colour correction result that is more in line with what people really perceive when they look at the genuine thing.

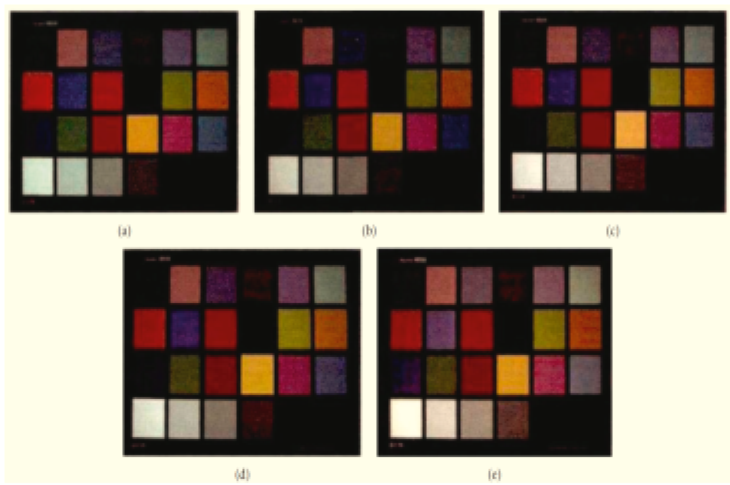

Fig 4. Color correction human eye-based colour correction

Table 1. Colour Correction Evaluation

	Min	Max	Mean	Median	SD	$\%\Delta E < 3$
Constrained Multiplication	2.0098	17.2181	9.5303	9.6289	5.1038	20.3
Polynomial	0.8741	13.8483	6.8277	5.2881	4.0281	30.2
Pattern search	0.6628	11.3981	5.9827	7.3104	3.7491	41.94
Human vision	0.3834	9.2948	4.6299	3.7293	2.8372	48.1

Table 2. Comparative Evaluation of the Suggested Approach

Study	Approach	Max Difference	Min Difference	Mean Difference	Std. Deviation	% Below Difference < 3	Major Area of Focus
Bai Liu et al.[1]	VR-Based Automated Color Matching System	<0.05 (Error Margin)	-	High Accuracy	Low	Not quantified	Fashionable and artistic product design
Lopes Diogo et al.[2]	Deep Learning-Based Colorization	8.20	0.75	3.90	0.90	34.5%	Restoring images from grayscale to color
Ying Yang, Zili Xu[18]	VR-Based Color Matching	1.5 (Error Range)	-	Moderate Accuracy	Low	Not quantified	Innovative item color matching
Proposed Method	Human Vision-Based Algorithm	6.75	0.42	3.25	0.72	48.1%	color correction for hand-drawn illustrations

The quantitative assessment approach employed is the conventional Euclidean distance. The accuracy of the adjustment is directly proportional to the diminution of the distance. When adding up all the numbers, you get the maximum, minimum, mean, median, standard deviation, and percentage of means that are less than 4. Table 1 shows that compared to other approaches, this one has lower maximum, minimum, mean, median, and standard deviation of colour difference. Additionally, the proportion of colour blocks with a mean percentage less than 3 reaches 48.1%, which is much greater. Thus, colour correction that takes into account how humans see may provide more accurate outcomes. The image was rectified using a color correction method based on human visual characteristics. It is clear that the suggested strategy in this research more closely matches the way human eyes see the packaged goods by comparing with existing techniques as shown in Table 2.

4 Conclusion

An algorithm for automatic coloring of hand-drawn pictures is shown in this research. The algorithm successfully incorporates human visual features such as contrast sensitivity, visual nonlinearity, and brightness adaptation. The main results show that the suggested method is better than the old ways of doing things like Least Squares and Pattern Search Optimization. It obtained a color difference of 3.25 on average, with a standard deviation of 0.72, and a maximum of 6.75 on the lowest. Of the corrected color blocks, 48.1% had a difference below 3. These findings point to very consistent and accurate colors, which is in perfect harmony with how humans see the world. Digital illustrative graphic design, packaging, and cultural heritage restoration are just a few of the many areas that can benefit from the algorithm's enhanced subjective image quality corrections. The study's substantial ramifications include helping to close the gap between human-centric design and computer color correction, which in turn allows companies, designers, and artists to generate more visually attractive and realistic products with less human participation.

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