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Discussion on the Intermingling of Artistic Expression and Technical Application of Numerical Simulation Methods in Visual Communication Design

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ABSTRACT

This paper studies the application of numerical simulation in visual communication design from two perspectives of artistic expression and technical application, and explores the facilitating effect of numerical simulation method on the intersection of artistic expression and technical application. Based on the improved K-means method, the extraction of the main color of the image is completed, and the extraction results are input into the color matching model integrating visual aesthetics as the label of the color palette. The visual communication design method is constructed based on image processing technology, and the method is realized through numerical simulation, so as to test the effectiveness of the technology application in visual communication design. Compared with other algorithms, the improved K-means algorithm in this paper can effectively realize the extraction of the main color of the image. The visual aesthetics score in the color matching model fluctuates within the range of [1.10,7.09], and the main color extraction result of the improved K-means algorithm combined with this score as a parameter can realize the coordinated matching of colors. At the same time, the visual communication design method based on image processing technology shows superior performance in terms of communication success rate and communication consumption time. According to the role of numerical simulation method in artistic expression and technical application, this paper explores the intermingling of artistic expression and technical application, highlighting the important influence of numerical simulation method in the process of intermingling.

Keywords: Numerical simulation method, improved K-means, image processing, artistic expression, visual communication design

1. Introduction

With the progress of science and technology, the development, application, promotion and popularization of digital technology, people's access to information has gradually expanded from

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traditional media such as newspapers, magazines, radio, television, etc., to the Internet, cell phones on a variety of APPs, the gradual digitization of a variety of traditional media, such as digital audio broadcasting, digital high-definition television, digital cinema, etc., as well as based on the digital technology of the new communication tools such as eBook, PDA, PS2 and XBOX game consoles and other visualized “new media” [1-3].

The arrival of the new media era has had an impact on all walks of life in society, bringing challenges to the industry while also adding more opportunities, and the traditional industry must make changes under the impact of new media in order not to be abandoned by the times [4-5]. The progress of society has made people's pursuit of vision qualitatively improved, which also prompts the visual communication art design industry needs to make continuous progress to meet the current pursuit of people for art design [6-7]. Variability is one of the important characteristics of visual communication art design in the new media environment, whether from design elements to design style, the forms are diverse and varied, and the varied art design can better satisfy people's visual enjoyment [8].

In the new media environment, the versatility of visual communication art design elements is particularly prominent. Traditional visual design elements can be utilized more flexibly with the help of new media [9]. Text can be presented through dynamic typography, font deformation and other ways to present a richer visual effect, graphics can be achieved through 3D rendering, dynamic generation and other technologies to achieve a more three-dimensional, vivid display, and color can be processed through gradient, transparency and other ways to create a richer color hierarchy [10-11]. These varied design elements make visual communication art design more attractive and infectious in the new media environment [12]. Design style also presents the characteristic of variability in the new media environment. Traditional design styles have been newly developed and evolved under the influence of new media [13]. At the same time, many emerging design styles have emerged, which not only have a unique visual impact, but also can be combined with new media technology to form a more diverse visual presentation [14-15].

In the new media environment, visual communication art design is no longer limited to traditional print media, but expanded to a variety of forms such as digital media. Interactivity, as a core characteristic of new media art, provides designers with more creative space [16-17]. Designers can enhance the audience's sense of participation and immersion by allowing them to participate and interact with the works through interactive design. This interactive design approach makes visual communication art design more vivid, interesting and attractive [18]. Among them, dynamic interactive design is a direct expression of interactivity. Under the new media environment, dynamic interactive design becomes an important expression of visual communication art design. Designers can create visual effects with a sense of motion and rhythm to attract the audience's attention through dynamic graphics, animation and other elements [19-20]. At the same time, designers can also set up triggering conditions to allow the audience to interact with the work through clicking, sliding and other operations, thus bringing an immersive experience. In addition, with the arrival of the era of big data, inductive interaction design has gradually developed. Sensor interaction design is another common way of interactive design. Designers can utilize sensor technology to allow viewers to interact with the work through touch and other actions. This design method not only enhances the audience's sense of participation, but also makes the work more vivid and interesting [21-22].

The concept and form of visual communication have been born for a long time, and it is revealed in literature [23] that the form of visual communication has been changing with the development of new materials and technologies, which can be traced back to the cuneiform script at the earliest, and then to metal movable type printing, and then to the printing revolution, which has pushed forward the popularization, diversification and rapidity of visual communication. Visual communication with the rapid development of technology at the present time also has new theories and technologies to support, in the literature [24] describes the innovation and development of visual communication design in the context of digital media art, summarizes the design characteristics of visual communication design art in this context, and gives some innovative development suggestions. Literature [25] talks about the role played by computer-aided design in the field of visual communication, pointing out that computer technology can assist the creators of art design to create art works with more distinctive visual effects and richer images, and at the same time, the computer-aided visual communication design technology also has the advantages of simple operation and easy to be modified, and it is believed that the courses in the field of visual communication and other fields of art and design need to be constructed and vigorously promoted computer-aided It is believed that courses in visual communication and other art design fields need to build and vigorously promote computer-aided art design courses. Literature [26] discusses practice-oriented visual communication iconicity research, which is mainly divided into two approaches focusing on the design process and focusing on the characteristics of the visual communication design object, both of which are different, but both of which aim at providing visual perception to the target object. At present, the practice of visual communication art mainly includes art creation, public relations and marketing, and communication and interaction between young people, for example, literature [27] tries to combine the traditional Chinese ink elements with the practice of modern Chinese visual communication design, in order to explore the characteristics of the visual language of traditional ink art in the context of the Internet, and to show the simple beauty of ink art. Literature [28] reveals that graffiti artists can obtain more graffiti visual communication design elements and materials through cloud computing and IoT technology, which makes graffiti art more artistic and creative, and brings stronger visual impact. Literature [29] discusses the visual development of emoji, which is mainly used in the trendy communication between young people and students, marketing and service feedback of enterprise companies, and tries to discover reasonable teaching and learning design methods of emoji to realize interesting teaching and learning through emoji sharing visual. Literature [30], combined with cases of PR marketing practice, specifies that visual communication design forms are efficient in information processing, have a strong attraction to the audience, and at the same time are more likely to present high-quality visual information perception effects.

This paper gives a brief introduction to the concept and form of visual communication design and analyzes the application of numerical simulation method in visual communication design. Based on color matching and image processing technology, it explores the numerical simulation simulation effect of numerical simulation method in the artistic expression and technical application of visual communication design. Aiming at the defects of the traditional K-means method, this paper proposes an improved K-means method based on density, and judges the extraction results by comparing the similarity between the main color image and the input image. Visual aesthetics is quantified using eye movement behavior measure, and a palette visual aesthetics evaluation model is constructed using visual aesthetics parameters and the primary color palette of the corresponding image. The image translation model is introduced to compress the image features through global average pooling, and the color matching model integrating visual aesthetics is constructed by combining the image primary color extraction results, and the validity of the model is examined through numerical simulation. Based on the image processing technology, the visual communication partition model is established, and the internal classification of images is completed by coefficient expression in the partition model. Use the higher order information to establish the visual communication feature function and calculate its probability distribution, and extract the local feature information of the graphic through computer algorithm. Combining the image processing algorithm based on edge feature design forms the visual communication design method. According to the numerical simulation results of artistic expression and technical application, this paper focuses on the key role of counting numerical simulation method on the integration of artistic expression and technical application in visual communication design.

2. Visual Communication Design Overview

2.1. Visual Communication Design

Visual communication design refers to the design that utilizes visual images to convey information and creatively compose and convey visual information [31], which undertakes the task of visual translation, utilizing some visible visual carriers to convey some information or content. Visual communication design is a design integrating artistry and practicality, and the works should be created under the premise of "human-oriented". The scope of modern visual communication design has been enlarged under the promotion of digital technology, and the scope of visual communication design is extremely wide, which is categorized according to the dimension as two-dimensional design, such as typeface design, logo design, poster design, etc., and three-dimensional design, such as display design, packaging design, etc., as well as four-dimensional design, such as animation design and stage design, etc.

2.2. Forms of visual communication design

2.2.1. Visual images.Visual images include graphics and images, and so far there are two forms of expression: static and dynamic. Static images have existed since the beginning of design development, and they are also the most common form in visual communication design, which are widely used. Static images are designed to impress the audience through static drawings, texts, symbols, etc. and color matching, so as to attract people's interest. Dynamic images appear later than static images, with the development of science and technology, the emergence of new media, in recent years to add dynamic image elements of visual communication design works more and more, it meets the needs of modern development, in line with people's aesthetic needs. Dynamic images are visually easier to catch the audience's attention than static images, and some of them are accompanied by music, so that the audience can have a more comprehensive experience in the visual and auditory aspects.

2.2.2. Visual semantics.The fast-paced social life environment and the speed of information dissemination are getting faster and faster, and people are more likely to accept information in visual form. Through visual elements such as visual semantics, form and color, people can get information easily and quickly. Different graphics have different symbolic meanings, and expressive graphics, as an important visual symbol, can be used to convey information, communicate emotions, and embody a unique aesthetic meaning. For example, the heart often represents the meaning of love, the olive branch represents peace and so on. Different colors contain different emotions and have different symbolic meanings. For example, red symbolizes revolution, prohibition, enthusiasm, exuberance, etc., green symbolizes germination, vitality, hope, etc., color and human psychology are closely related.

2.3. Application of numerical simulation methods in visual communication design

2.3.1. Level of artistic expression.Numerical simulation methods provide a rich means of artistic expression for visual communication design. By simulating natural phenomena such as light and shadow, water flow and other natural phenomena, designers can create realistic virtual scenes to enhance the realism and infectiousness of the design. In addition, numerical simulation methods can also be used to simulate the animation effects of character movements and expressions, making the character image more vivid and three-dimensional. For example, in movie animation, designers can use numerical simulation methods to simulate the muscle movement and expression changes of the character, making the character image more realistic and expressive. At the same time, by adjusting the parameters and algorithms, designers can also create a unique artistic style to meet different aesthetic needs.

2.3.2. Technology application level.The application of numerical simulation methods in visual communication design is not only limited to artistic expression, but also involves technical aspects. Through numerical simulation methods, designers can make accurate prediction and optimization of design works and improve the efficiency and quality of design. For example, in virtual simulation, most of the scene modeling is 3D reconstruction based on data acquisition of the scene. The constructed virtual scenes are generally applied to reproduce the scene or perform on-site simulations, such as virtual driving, virtual soccer, and so on. These applications not only improve the practicality of design, but also provide more creative inspiration for designers.

3. Numerical Simulation Methods in Visual Communication Design for Artistic Expression

As mentioned before, the artistic expression of numerical simulation methods in visual communication design is diverse and rich in means. This section will focus on the artistic expression of numerical simulation method in color matching. The color matching and graphic design are completed by algorithms and simulated based on numerical values, so as to verify the effectiveness of the algorithms in this section and the important role of numerical simulation methods in visual communication design.

3.1. Image primary color extraction based on improved K-means

3.1.1. Selection of color space.Compared with RGB, the rest of the HSI color space, HSV color space and Lab color space need to carry out the corresponding spatial conversion, and the calculation is relatively complex, take HSV as an example, the HSV color space model is represented by 3 attributes. Where H indicates the hue, taking the value of 0-360°. S represents saturation, which refers to the depth of the same color. V represents brightness, which refers to the degree of lightness or darkness of a color, and takes the value of 0-1, where the darkest is 0 and the brightest is 1. The process of converting the RGB -space to the HSV-space is as follows: firstly, r,g,b is normalized to a number between 0 and 1, and then converted according to the following steps:

$\max = \max(r,g,b)$, $\min = \min(r,g,b)$, $mid = v - \min$.

Let's say $r' = \frac{v-r}{mid}$, $g' = \frac{v-g}{mid}$, $b' = \frac{v-b}{mid}$.

If $r = \max \& g = \min$, $h = (5+b') \times 60$.

If $r = \max \& g \neq \min$, $h = (1-g') \times 60$.

If $g = \max \& b = \min$, $h = (1+r') \times 60$.

If $g = \max \& b \neq \min$, $h = (3-b') \times 60$.

If $b = \max \& r = \min$, $h = (3+g') \times 60$.

Other cases $h = (5-r') \times 60$, $s = mid / v$, $v = \max$.

The model cannot directly use the values of the 3 dimensions for K-means clustering, and requires good coordination between the 3 components. For example, when V tends to 0 or 1, the color remains essentially unchanged no matter how S and H change, limiting the direct calculation of the Euclidean distance, and setting the HSV space colors $C_i = (h_{i,}, s_i, v_i)$ and $C_j = (h_j, s_j, v_j)$, the similarity distance d_{ij} for colors C_i and C_j:

$$d_{ij} = 1 - \sqrt{(h_i' - h_j')^2 + (s_i' - s_j')^2 + (v_i - v_j)^2} \Big/ \sqrt{5} \tag{1}$$

Where the values of $h_i' = s_i \cosh_i$, $s_i' = s_i \sinh_i$, $d_{ij} \in [0,1]$ and d_{ij} are closer to 1, the more similar the two colors are.

The RGB color space model is selected for the experiment, and the clustering is done directly after a simple normalization process, while in the final determination of the clustering results, the data are transformed into HSV before the determination.

3.1.2. Density-based initial point selection.Taking the density-based improved K-means algorithm as an example [32], it is first necessary to calculate the average distance of the data points in set D:

$$avgDist = \frac{\sum_{i=1}^{n}\sum_{k=1}^{n}\sqrt{\left(x_{i1}-x_{j1}\right)^2+\cdots+\left(x_{ik}-x_{jk}\right)^2}}{1+2+\cdots+n} \tag{2}$$

where n is the number of data points and k is the data dimension. Then the distribution density of each data is calculated. Then the densities of the data are rearranged according to the density size to get a new set D'.

3.1.3. Density-based optimization of extraction results. In order to improve the defects of K-means algorithm, this paper adopts the density-based clustering result improvement method.

a) set a threshold, using the traditional K-means algorithm for experiments, if the first clustering of a cluster in the amount of data is less than the threshold, then stop the iteration and re-select the initial clustering center, which avoids the problem of the initial clustering center falls in the discrete region, can be more stable clustering results.

b)Calculate the value of d_{ij} between the final obtained clustering center and the other points in the cluster, and if the number of points satisfying $d_{ij} > 0.9$ is more than 25% of the total number of points in the cluster, it is judged to be qualified, and if not, it is directly judged to be unqualified, and skip to step (c).

c) Calculate the point that has the highest number of points in its cluster that satisfy the similarity $d_{ij} > 0.9$ with other points, and use this point as a new cluster center, and the points that satisfy the above conditions are used as the member points of this new cluster, and calculate the average value as the final cluster center.

d) The original old cluster removes the points of the new cluster produced by step (c), and the remaining points form a new cluster, using the mean value as the clustering center, and repeating steps (b)-(d), but the threshold value keeps the original amount without any consequent reduction, until no new cluster is produced, and the remaining points are thrown out as noise points.

3.2. Color matching algorithm incorporating visual aesthetics

3.2.1. Visual aesthetics.Since the human eye is always attracted to more visually appealing objects, the quantification of visual aesthetics using eye movement behavioral measures is an important technical tool in this field. In the process of quantifying visual aesthetics using eye movement behavioral measures, the three most important eye movement behavioral indicators are average gaze time, average number of gaze points, and first gaze time, which reflect the visual comfort, visual attractiveness, and visual impact of the test image or video, respectively. Taking the average gaze time as an example, its calculation formula in the eye tracking experiment is shown in equation (3):

$$T = \frac{\sum_{i=1}^{n} T(AOI)}{n} \tag{3}$$

Eq:

n - number of test images or videos.

$T(AOI)$ - test time for delineating the region of interest in the eye movement experiment.

In visual search, targets with visual aesthetic appeal usually receive more gazes, and the corresponding eye movement behavior indicators include average gaze time, average number of gaze points, and first gaze time.

Using eye movement behavior indicators to construct visual aesthetics data flow, the above three eye movement behavior indicators are normalized before processing, in which the average gaze time and the average number of gaze points are positively correlated with the degree of visual aesthetics favoritism, taking the average gaze time as an example, and the processing method is defined as follows:

$$h' = \frac{h - h\_\min}{h\_\max - h\_\min} \tag{4}$$

Eq:

h - the current data to be processed before normalization.

$h\_\min$, $h\_\max$ - the minimum and maximum values of the average gaze time, respectively.

The first gaze time measure is negatively correlated with visual aesthetics favoritism in the interaction task, which is processed as defined below:

$$j = 1 - \frac{j - j\_\min}{j\_\max - j\_\min} \tag{5}$$

Eq:

j - the current data to be processed before normalization.

$j\_\min$, $j\_\max$ - the minimum and maximum values of the first gaze time, respectively.

The visual aesthetic parameter W is shown in equation (6):

$$W = (\alpha h + \beta i + \gamma j) \times 10 \tag{6}$$

Eq:

W - the visual aesthetic parameter for fusing three different eye movement behavior data, taking values between $[0,10]$.

α, β, γ - weights of three different eye movement behavior data.

Of these, the three weights are set differently depending on the visual task, and $\alpha = \beta = \gamma = 1/3$ is used in this chapter to calculate the visual aesthetics score W.

3.2.2. Image translation model.The image translation model is a manifestation of a conditional generative adversarial network in the image translation task. The image translation model is a conditional generative adversarial network with U-Net and Markov discriminator as generator and discriminator respectively, whose generator input is a real sample image x, and its output is a generated image $G(x)$. Since the discriminator needs to judge the authenticity of the output image of the generator, the input of the discriminator is a pair of images consisting of the generated image $G(x)$ and the real image.

In addition, the Pix2Pix network model introduces $L_1\ Loss$ to judge the image globally on the basis of CGAN, as shown in equation (7):

$$G^* = \arg\min_G \max_D L_{cGAN}(G, D) + \lambda L_{L_1}(G) \tag{7}$$

Eqs:

G, D - represent generator and discriminator respectively.

$L_{L_1}(G)$, λ - represent the weights of $L_1\ Loss$ & $L_1\ Loss$ respectively.

Where $L_1\ Loss$ is defined as defined below:

$$L_{L_1}(G) = E_{x,y,z}\left[\|y - G(x,z)\|_1\right] \tag{8}$$

Eq:

G - generator.

x, y, z - denote real samples, conditional probabilities, and random noise, respectively.

The loss function of Pix2Pix is shown in equation (9):

$$
\begin{aligned}
& L\left(G_{\min }, D_{\max }\right)=E_{x \sim p_{data}(x)}[\log D(x \mid y)] \\
& +E_{z \sim p_z(z)}[\log (1-D(G(z \mid y)))]+\lambda L_{L_1}(G)
\end{aligned} \tag{9}
$$

3.2.3. Color matching model incorporating visual aesthetics. A palette visual aesthetic evaluation model is constructed using the visual aesthetic parameters with the primary color palette of the corresponding image, and the evaluation model is used to score the input palette and subsequently optimize the loss function of the Pix2Pix backbone network using this scoring value. The evaluation model in this chapter uses the SE-Inception V3 network model [33], which compresses the image features through global average pooling and scores the probability distribution of the image aesthetic quality scores, and trains the scoring model using the extraction results of the primary color extraction method constructed in the previous section as the labels of the corresponding palettes.

The loss function of the backbone network Pix2Pix is updated using the aesthetic scores of the color palette, and the aesthetic loss function $S(G)$ and the total loss function of the intelligent color matching algorithm incorporating visual aesthetics established in this paper are shown in Eq. (10) and Eq. (11), respectively:

$$S(G)=10-Score \tag{10}$$

$$
\begin{aligned}
& L\left(G_{\min }, D_{\max }\right)=E_{x \sim p_{data}(x)}[\log D(x \mid y)] \\
& +E_{z \sim p_z(z)}[\log (1-D(G(z \mid y)))]+\lambda L_{L_1}(G)+\gamma S(G)
\end{aligned} \tag{11}
$$

Eqs:

$Score$, 10 - denote the score of the visual aesthetic scoring model of the color palette and the full score of the aesthetic evaluation, respectively.

γ - the weight of $S_{(G)}$.

4. Technical application of numerical simulation method in visual communication design

The application of numerical simulation method in visual communication design is not only limited to artistic expression, but the technical application can deal with the problems of image processing and image synthesis in visual communication design, which provides significant convenience for visual communication design. In this section, the visual communication design method will be constructed through image processing technology and the technical application of numerical simulation method will be illustrated through numerical simulation simulation to illustrate the important role of numerical simulation method in visual communication design.

4.1. Modeling of visual communication zoning

Typically, the image to the human eye is stored as a continuous image, at which point a vector representation of the two-dimensional image can be created, i.e:

$$g\left(x_i y_i\right)=\left\{g_r\left(x_i, y_i\right), g_g\left(x_i, y_i\right), g_b\left(x_i y_i\right)\right\} \tag{12}$$

where $g_r\left(x_i, y_i\right)$, $g_g\left(x_i, y_i\right)$, and $g_b\left(x_i, y_i\right)$ denote the vector function of the three primary colors of red, green, and blue in the image signal, $g\left(x_i, y_i\right)$ denotes the signal expression of the original image, and x_i and y_i denote the function of light intensity and spatial coordinates in the image, respectively. When extracting the feature description, the descriptor can be recorded as:

$$G_K=\left[g_1, g_2, \cdots, g_n\right] \tag{13}$$

The set needs to be guaranteed $G_K \in H^{b \times p}$, where b denotes the dimension of the image features and P denotes the number of image features. In the process of clustering the visual communication partitions, the set of visual communication partitions can be represented as:

$$F_K = [f_1, f_2, \cdots, f_n] \tag{14}$$

With this collection of visual communication partitions, it is possible to keep every element in the form of a feature inside a clustering center. Encoding all the clustering centers separately and summarizing each successive feature null separately in the form of a collection will reduce the quantitative knowledge difference. The error in clustering is calculated as:

$$D_{s-u} = \frac{e^{\left(-\frac{\|d_x - d_e\|^2}{\delta_k}\right)}}{\sum_{i=1}^{n} e^{\left(-\frac{\|d_x - d_e\|^2}{\delta_k}\right)}} \tag{15}$$

where D_{s-u} denotes the distance from any feature null s to the clustering center u; d_x and d_c denote any two features with similar distances, respectively, and δ_k denotes the clustering weight parameter.

4.2. Extracting local feature information of an image

Based on the visual communication partitioning model, the internal categorization of images can be accomplished in it in the form of coefficient expressions. Establishment of coded coefficient features:

$$\begin{gathered} \arg\min \left\| p_x - H^T \right\|^2 + k_p \sum_{i=1}^{n} |h(i)| \\ s.t. \sum_{i=1}^{n} h(j) = 1 \end{gathered} \tag{16}$$

Where: $\left\| p_x - H^T \right\|^2$ denotes the constraint error in the process of reconstructing the local features of the image. It is necessary to make $\sum_{i=1}^{n} h(j) = 1$ while ensuring that its value is as small as possible. k_p denotes the weight parameter that balances the constraint coding with the dictionary coefficients. In the reconstruction constraints of feature encoding, the non-convex features of the problem can be solved for constructing the set of local constraint linear encoding. In this case, it is necessary to reduce the efficiency of the cost function by means of a support vector machine to delimit a hyperplane in the feature plane:

$$f(a): a_k = H^T k + k_0 = 0 \tag{17}$$

where $f(a)$ denotes the data discriminant model of the hyperplane, a_k denotes the parametric features of the hyperplane, H^T denotes the category label of the distance matrix, and k_0 denotes the separation degree of the samples. When the data is completely separable, a hyperplane that can satisfy all data points can be found. At this point, the higher order information is used to establish a visual communication feature function and calculate its probability distribution, and then the local feature information of the graphic can be extracted by computer algorithms. The weights of Gaussian coding [34] are calculated as:

$$w_{ij}(f) = \left(\frac{\sqrt{M_n}}{\sum_{i=1}^{n} N_i} \right)^{\alpha - 1} \tag{18}$$

where $w_{ij}(f)$ denotes the coding format of the Gaussian distribution under constrained weight conditions, M_n denotes the coding vector of the clustering centers, and N_i denotes the zero-order information smoothing factor.

4.3. Designing image processing algorithms based on edge features

The frequency of occurrence of pixels of a certain gray level in an image can be obtained by dividing a digital image in a computer into several grids using sampling and quantization, and calculating the luminance value of the simulated image in each grid:

$$D(t_k) = \frac{N_i}{K_n} \tag{19}$$

where $D(t_k)$ represents the frequency of occurrence of pixels of a certain gray level in the image, t_k represents the gray level quantization value, N_i represents the total number of pixels of the brightness value of level i, and K_n represents the total number of pixels within that image. By adjusting the gray levels within an image, an image with a more prominent contrast effect can be obtained. In addition to this, it is also necessary to obtain the transformation relationship within the image by using the gray scale transformation, i.e.:

$$f_i = G(t)D(t_k) \tag{20}$$

Where, f_i represents the gray scale transformation function within the image and $G(t)$ represents the normalization index of the image transformation within the region. Using this transform function, the number of gray values with a gray scale distribution of 50 to 100 within the image can be concentrated in an interval.

5. Experimental results and analysis

5.1. Main color extraction

5.1.1. Simulation analysis of 3-dimensional data. A set of 3-dimensional data is used as an example to illustrate the implementation process of the optimization algorithm. The data has two dense data regions and one data region with a ring-like distribution, using the traditional K-means clustering algorithm to take three initial clustering centers, the most ideal clustering results are shown in Figure 1. The ideal clustering result using the density-based improved K-means algorithm is shown in Figure 2. The clustering result of the improved algorithm based on traditional K-means in this paper is shown in Fig. 3. Among them, the 5th class is the thrown noise point. In this paper, the density is used in the processing of the final clustering results, the scope of action is only limited to a cluster rather than the overall data, for the density of the calculation is reduced, saving the algorithm's running time and obtaining excellent clustering results.

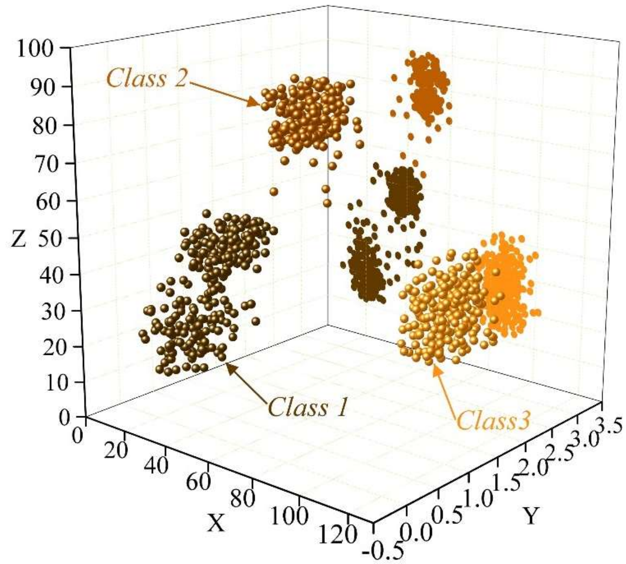

Fig. 1. Clustering result of common K-means

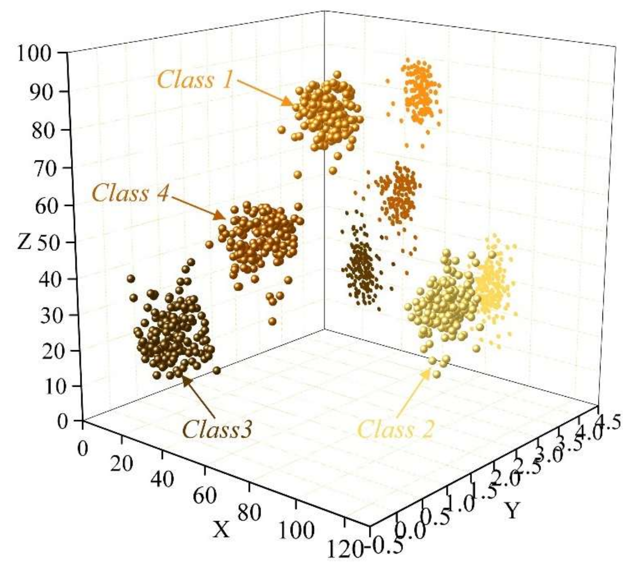

Fig. 2. Clustering result of improved K-means

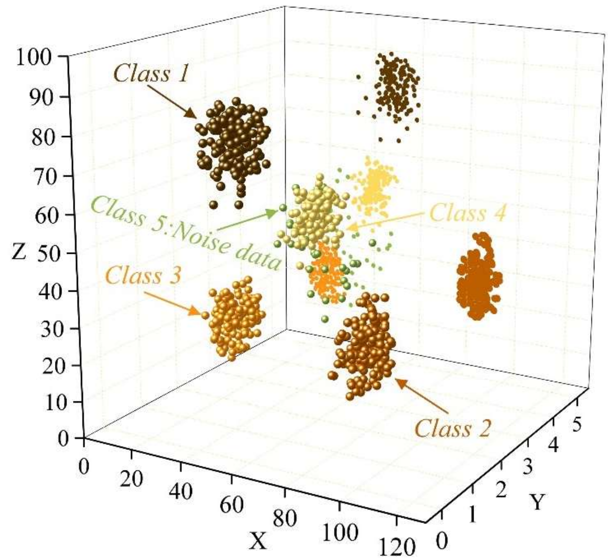

Fig. 3. Clustering result of this article's algorithm

5.1.2. Comprehensive evaluation analysis. The platform for the implementation of the algorithms in this paper is an Intel(R) Core(TM) 2 Duo CPU E8400-3.00GHz central processor, 1.00GB capacity memory, and MATLAB R2010a development environment. The algorithm was tested using a large number of images, but due to the limitation of the length of the article, the test results of only one image are presented here in Fig. 4. Figure 4 shows the primary color extraction results under different spatial aggregation thresholds ths, in which the first row of the first image is the input original image, the second to the fifth images are using the density-based improved K-means algorithm (Algorithm A), the traditional K-means algorithm (Algorithm B), the histogram peak-based filtering algorithm (Algorithm C), and this paper's algorithm (Algorithm D), and the second row is the algorithms of the 4 obtained primary color labels. Obviously, if the threshold is too small, noisy pixels may be extracted too much, resulting in false detection of the primary color. If the threshold is too large, it may lead to main color miss-detection, although this is relatively rare. It has been verified through a large number of experiments that when this threshold is taken as 0.6, the effect of noise on the primary color extraction results can be eliminated.

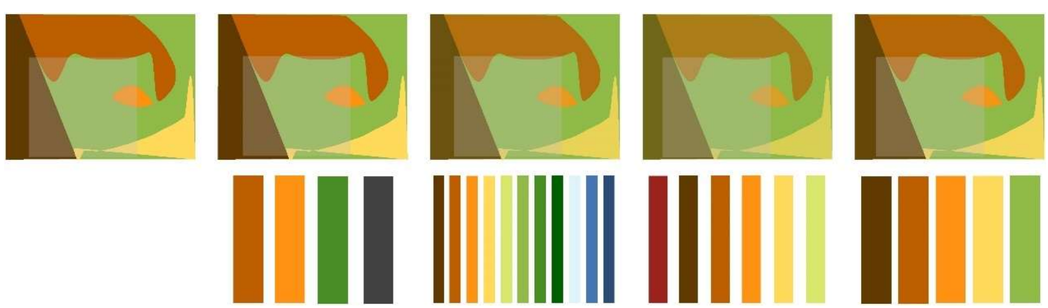

Fig. 4. Examples of simple artificial scene

Table 1 shows the scores given by the evaluation model proposed in this paper for the primary colors extracted by each algorithm as well as the statistics of the luck time. All sets of test data show that the algorithms in this paper have the highest final scores. The average score of this paper's algorithm is 0.881, which is 1.401 times that of Algorithm A, 1.491 times that of Algorithm B, and 1.459 times that of Algorithm C, respectively. The results show that this paper's algorithm is effective and can excellently complete the task of main color extraction of images.

Table 1. Performance data of dominant color extraction algorithms

Image	Algorithm A		Algorithm B		Algorithm C		Algorithm D	
	E	Time/s	E	Time/s	E	Time/s	E	Time/s
Experiment1	0.632	23.86	0.451	34.86	0.553	23.53	0.836	6.84
Experiment2	0.617	24.83	0.584	39.83	0.586	24.84	0.903	4.28
Experiment3	0.653	22.19	0.662	33.77	0.634	23.97	0.884	6.17
Experiment4	0.628	23.37	0.597	35.42	0.628	25.09	0.857	5.39
Experiment5	0.619	24.73	0.639	36.09	0.606	22.48	0.892	6.03
Experiment6	0.627	22.39	0.612	37.16	0.617	23.94	0.913	4.72
Mean	0.629	23.56	0.591	36.19	0.604	23.98	0.881	5.572

5.2. Color matching

On the basis of realizing the main color extraction, this subsection carries out experimental analysis on the constructed color matching model to verify the effectiveness of this paper's color matching model integrating visual aesthetics in the artistic expression of visual communication design.

5.2.1. Color palette visual aesthetics score. From the palette dataset, 2000 pictures are selected as experimental material, the display angle is front view, all pictures are removed the background color, only the main color results extracted by the main color extraction algorithm are retained. The different pictures have the same location in the screen and are similar in size. The equipment used for the experiment was a Tobii ProFusion 250Hz eye-tracking device with a sampling frequency of 300 Hz. 150 school students were invited to participate in the experiment, aged between 21-23 years old, with a male to female gender ratio of 3:5, all of whom were right-handed, and all of whom had good visual acuity after spectacle correction, with no color-blindness and no color-weakness. During the experiment, the subjects completed the calibration of the eye-tracking device according to the video prompts of the eye-tracking device. After completing the calibration, the subjects officially entered the eye movement experiment step. Subjects would carefully observe the front view for 10,000 ms according to the prompts displayed on the screen, and focus on the color area of interest until the end of the experiment. After completing the experiment, eye movement hotspot maps were generated based on the subjects' regions of interest for different colors, and the results are shown in Figure 5.

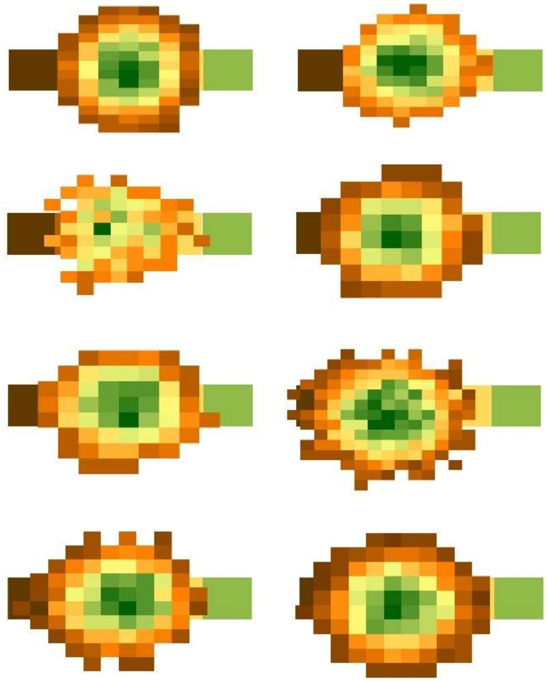

Fig. 5. Heat map of partial eye tracking experiment results

Some key statistical indicators in the eye movement experiment are shown in Table 2. From the table, it can be seen that the maximum values of average gaze time, average number of gaze points and first gaze time are 1381.42, 6.42 and 583.69, respectively, and the minimum values are 375.98, 1.97 and 135.74, respectively. Meanwhile, the average gaze time and the first gaze time are 813.94ms and 253.73ms, respectively, which indicates that the eye movement behavior of the subjects has certain fluctuation.

Table 2. Key metrics for eye tracking experiments

Key indicator	Average fixation time/ms	Average fixation point number	First sight time/ms
Maximum value	1381.42	6.24	583.69
Minimum value	375.98	1.97	135.74
First quartile	718.64	3.22	201.98
Median	829.43	3.58	229.46
Third quartile	938.17	4.13	272.85
Mean	813.94	3.72	253.73
Data upper limit	1271.39	5.89	415.86
Data lower limit	356.28	1.83	75.48

The visual aesthetics scores were calculated based on the results of the eye movement experiments and their data statistics W, and the eye movement behavioral indexes of some samples and their visual aesthetics scores were obtained as shown in Table 3. It can be seen that the visual aesthetics scores fluctuate up and down in the interval of [1.10,7.09] in the selected 20 samples.

Table 3. Eye tracking behavior indicators and visual aesthetic scores for some samples

Sample number	Average fixation time/ms	Average fixation point number	First sight time/ms	Visual aesthetics rating
Palette 1	989.33	4.23	190.45	6.85
Palette 2	759.26	3.44	251.47	4.53

Palette 3	622.10	3.10	284.36	2.35
Palette 4	852.05	3.26	235.51	5.84
Palette 5	704.05	3.76	269.13	4.66
Palette 6	763.10	3.18	210.87	5.87
Palette 7	624.83	2.61	381.87	2.63
Palette 1	930.99	3.20	204.20	6.25
Palette 8	860.82	3.07	209.47	5.31
Palette 9	778.82	3.35	226.53	6.04
Palette 10	768.68	3.49	182.92	6.84
Palette 11	801.28	3.76	224.05	6.8
Palette 12	854.24	4.53	203.36	7.09
Palette 13	673.31	4.23	389.06	1.30
Palette 14	796.69	2.65	337.56	3.56
Palette 15	700.21	2.27	281.58	5.02
Palette 16	540.46	1.73	380.86	1.10
Palette 17	956.33	3.95	176.79	6.72
Palette 18	790.48	3.32	245.71	5.22
Palette 19	862.36	3.66	251.70	5.07
Palette 20	989.33	4.23	190.45	6.85

5.2.2. Color experiment results.The network architecture for the experiments in this section uses a U-Net with an encoding-decoding structure, which contains 2 convolutions, 7 residual blocks, two transposed convolutions with a step size of 1 / 3, and a normal convolution that maps the color palette to an RGB image. Seven blocks were used for the training images. Instance Normalization is used. Where the discriminator network uses PatchNet computed based on image blocks of size 100 × 100. This discriminator structure based on image block computation has fewer parameters than the discriminator based on full-image computation, and can process images of arbitrary size in a fully convolutional manner. Second, to minimize model oscillations, the discriminator is updated using the history of generated images rather than the latest generated image. An image buffer is reserved for storing the image after primary color extraction.

The batch size of the experiment was 64 and the optimizer was chosen as Adam optimizer. The network was trained from zero with a learning rate l_r of 0.003. The number of model iterations was set to 1000, keeping the same learning rate for the first 500 epochs, and decaying linearly to 0 for the next 500 epochs.

The 2000 images described above were divided into a training set and a test set in the ratio of 7:3, yielding a total of 1400 training images. The training images are processed as color palettes according to the processing described above are inputted into the model to train the model and tested in the divided test set. Some of the experimental results are shown in Fig. 6, where the black part indicates the residual color palette. From the figure, it can be seen that the color matching model integrating visual aesthetics constructed in this paper can effectively supplement the residual colors in the dataset, and can be combined with the visual aesthetics scoring parameter and the image translation model to color match the images after the extraction of the main color. The method can successfully achieve the coordination of different colors through numerical simulation, significantly improve the harmony of color matching, and effectively highlight the artistic performance in visual communication design.

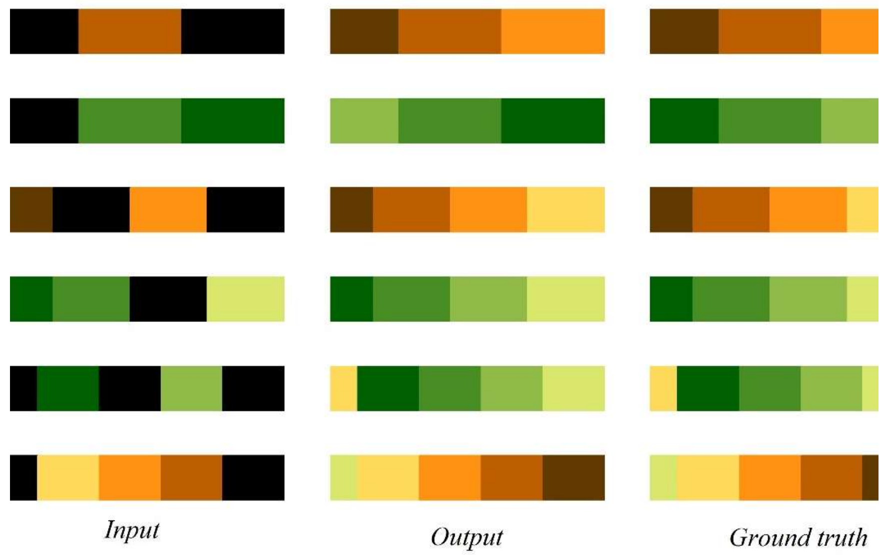

Fig. 6. Pairing results of Partial test sets

5.3. Technology applications

In order to verify the practical application performance of visual communication design based on image processing technology, an infrared frequency set flyer with a fast moving target is selected for verification. In order to enhance the validity of the experiments, the method of this paper (Method 1), the image visual communication method based on infrared spectrum (Method 2) and the image visual communication method based on virtual reality environment (Method 3) are tested in the experimental environment described in the previous section, respectively.

The success rate of visual communication of different methods is shown in Fig. 7. From the figure, it can be seen that the visual communication success rates of the methods in this paper are all above 96%, which is mainly because the methods in this paper transform the visual communication problem into an image processing problem, and because the image processing technique in this paper firstly constructs the visual communication partition and utilizes the method of local feature information extraction to make the target features more obvious, which improves the success rate of visual communication.

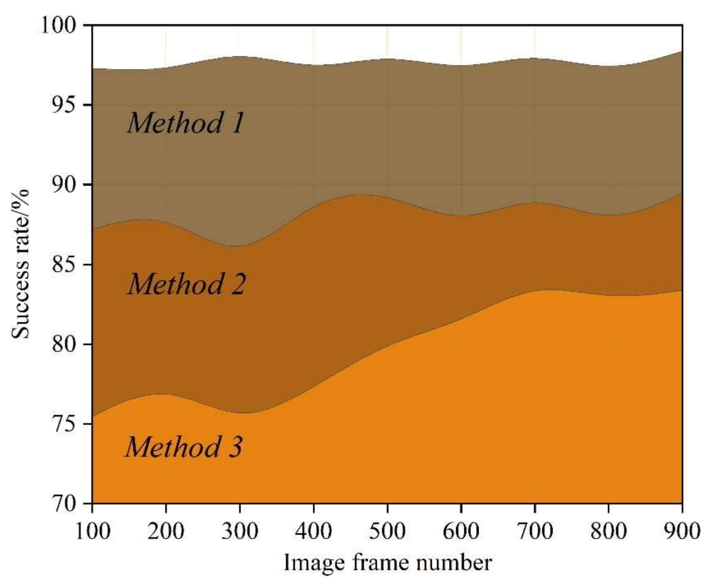

Fig. 7. Comparison of the success rate of visual communication in different methods

On this basis, the changes in conveying time with image size of different methods are tested and compared, and the comparison results are shown in Fig. 8. From the figure, it can be seen that with the increase of image size, the time required for visual communication of this paper's method does not change significantly, and the time required is significantly less than the other two methods. This is mainly due to the fact that the method in this paper transforms the original discrete coding method into the form of weighted processing in the process of establishing the visual communication partition, which improves the coding efficiency at the time of coding and significantly reduces the time of image processing as well as visual communication.

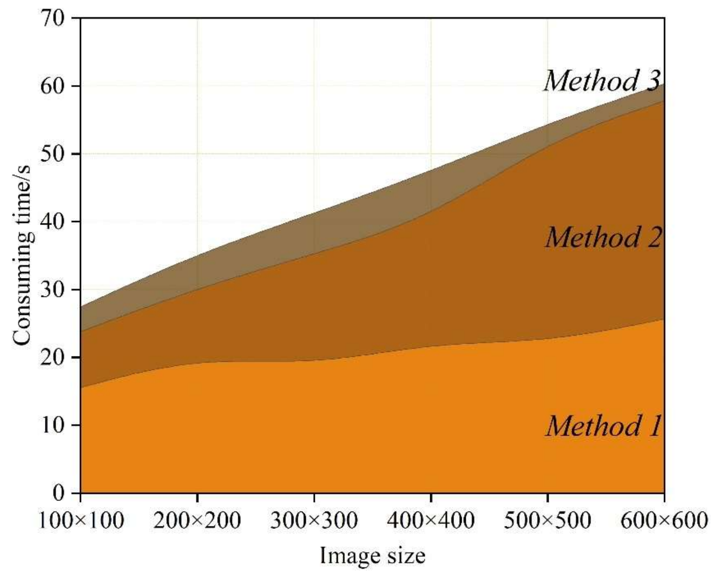

Fig. 8. The variation of communication time with size for different methods

Through the numerical simulation analysis of the numerical simulation method, this paper intuitively explains the good effect of applying technical means to visual communication design. The extraction of image features by processing technology and the establishment of visual communication partitions provide important tools for numerical simulation. Only through the numerical simulation method can the visual communication design method established in this paper be put into practice and the application effect of the algorithm be observed, so the numerical simulation method and its technical application is an important part of the visual communication design in this paper.

6. Intermingling of artistic expression and technical application

Numerical simulation is a means of realizing the deep integration of art and technology by constructing a virtual model or scene based on the accurate numerical analysis and simulation of various elements. Its core lies in transforming those abstract and difficult-to-quantify elements in visual communication design into calculable and manipulable numerical values, which can be presented and optimized by technical means. In today's era of rapid development of digitalization, the numerical simulation method plays an extremely crucial role in promoting the integration of artistic expression and technical application in visual communication design.

6.1. Visual presentation

In terms of visual presentation, numerical simulation achieves a close combination of artistic expression and technical application through numerical coding and simulation of visual elements such as color, shape and texture. Taking the production of movie special effects as an example, in order to create a realistic image of alien creatures, designers use numerical simulation to make detailed numerical settings for the shape and contour of the creatures, epidermal texture, color changes, etc. The numerical simulation is used to determine the geometric and numerical analysis of the body parts of the creatures. Through the geometric numerical analysis of the creature's form, the proportion and curve of its body parts are determined. Based on the spectral values of the colors, the skin tone and mottled colors are matched uniquely and in line with the sci-fi scenario. Target epidermal textures. Numerical values are used to simulate the effects of different roughness and glossiness. These precise numerical settings not only make the extraterrestrial creatures visually very artistic, to meet the audience's aesthetic expectations for the image of fantasy creatures, but also with the help of computer graphics technology to efficiently and accurately rendered on the screen to ensure that different playback devices can maintain a relatively consistent visual effect.

6.2. Interaction Design

In the field of interaction design, the numerical simulation method constructs a mathematical model of interactive feedback through the numerical processing of user behavioral data, which greatly enhances the integration of art and technology in interactive experience. For example, in the visual communication design of cell phone games, every action of the player, such as the position of clicking on the screen, the speed and direction of sliding, etc., will be transformed into corresponding numerical data. Visual communication designers utilize the counting numerical simulation method to design the character's action response, scene change effect and sound effect triggering mechanism according to these data. From the perspective of artistic expression, these visual interaction feedbacks can create a tense and rhythmic game atmosphere and enhance the fun and immersion of the game. From the perspective of technical reality, the numerical-based interaction model can run stably on different cell phone operating systems and hardware configurations, ensuring the compatibility and smoothness of the game.

6.3. Space design and presentation

Numerical simulation method has a unique integration strategy in the spatial design and display of visual communication design. In the design of virtual exhibition hall, through the numerical simulation of the size value of the exhibition hall space, the coordinate value of the placement of exhibits, and the intensity and angle of light, the designer can create a highly artistic and beautiful layout of the exhibition space. From the artistic conception, the numerical value is used to adjust the spatial relationship between exhibits and the contrast between light and darkness, so as to highlight the artistic characteristics and cultural connotation of the exhibits. From the technical level, these numerical design solutions can be easily realized in virtual reality devices or large screen display systems, providing an immersive viewing experience for the audience, both locally and remotely, as if they were physically present in the art atmosphere.

7. Conclusion

This paper mainly explores the important role of numerical simulation method in the process of integrating artistic expression and technical application of visual communication design. By constructing a visual aesthetics evaluation prediction model and combining the image primary color extraction results of the improved K-means algorithm, a color matching model integrating visual aesthetics is formed. The model can effectively supplement the residual part of the color label and form the output results with high color harmony. It fully demonstrates the effectiveness of the color matching model constructed in this paper, and the effective performance of the color matching results generated by numerical simulation method on the artistic aesthetics of visual communication design. The visual communication design method based on image processing in this paper has a visual communication success rate of more than 96%, which is significantly higher than that of image visual communication based on infrared spectrum. At the same time, this paper's method performs well in terms of the time needed for visual communication, and for images of different sizes, the time consumed for visual communication stably stays below 25s. Finally, this paper discusses the promotion role of numerical simulation in the integration of artistic expression and technology application from three dimensions of visual presentation, interaction design and spatial design and display, which illustrates the prospect of the wide application of numerical simulation in visual communication design.

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