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Research on Color Emotion Mapping and Character Adaptation Model for Animated Films Based on Multilayer Perceptual Machine

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Abstract Color has a regulating effect on human emotion, the author, in order to explore the emotion mapping effect of color in animated movies and its relationship with character suitability, introduces the multilayer perceptual machine model, constructs the adaptive color perceptual machine model and the multilayer perceptual machine color emotion recognition model. And the character suitability assessment model is constructed to explore the performance of animated movies in terms of color and character suitability. In the color emotion analysis of animated films, neutral tone, warm tone, and high brightness colors are closely related to neutral and positive emotions, while low brightness and cold tone colors are often related to negative emotions. Warm tones and high brightness colors are conducive to arousing positive emotions in moviegoers, while cold tones and low brightness colors are prone to arousing negative emotions in moviegoers. Red, green, blue, and purple tones are more likely to inspire pleasure in moviegoers. Black and white colors are easy to stimulate negative emotions. When there are 3~10 kinds of colors, the emotion of the picture tends to be positive. Taking the animated film "Journey to Dreamland" as the evaluation object, the film scored 4.17 points on the overall score of color and character suitability, and the viewers are more satisfied with the evaluation results of the color and character suitability of the animated film.

Index Terms multilayer perceptron, adaptive color perceptron, color emotion mapping, character adaptation

I. Introduction

Animated film is a fascinating art that presents a fictional world to the audience with vivid images, colorful colors and elaborate character modeling [1], [2]. In this virtual realm, the synergy of color and character modeling plays an indispensable role [3]. Color not only gives life and emotion to the picture, but also contributes to the character's personality shaping and emotional expression [4]. The use of color in animated films transcends the purely aesthetic value; it mobilizes the audience's emotional response through specific hues, contrasts and saturation to construct a specific emotional atmosphere and symbolism [5]-[7]. In animated films, the strategic use of color not only enhances the narrative depth, but also reveals the emotional complexity within the character and expresses the character's individual personality traits [8]-[10].

In addition, color can also serve as a cultural metaphor to reflect social expectations and prejudices of the characters, as well as the status and identity of the characters in different cultural and social contexts [11], [12]. Character modeling, on the other hand, is a vehicle for color to convey emotions and story clues through a character's appearance, features, and actions [13]. The wonderful design of character modeling often becomes a highlight of animated films, which not only enriches the character's personality, but also deeply reflects the character's character, emotion and story background [14], [15]. Therefore, color and character modeling complement each other in animated films, jointly promoting the development of the story and the emotional resonance of the audience [16]. By conducting research on color emotion mapping and character adaptation in animated films, it can provide new perspectives and strategies for the creation of animated films, promote wider discussion and understanding of the character traits of films, and at the same time can enrich the expressiveness and depth of animated films as an art form.

Starting from the theory of multilayer perceptual machine, the article explores the possibility of its application in color, and proposes a color perceptual machine with the help of 3D-LUT image processing tool. On the basis of the color perception machine, an adaptive color perception machine model is further constructed. In order to realize the link correspondence between color factors and emotional categories, the author embeds the dynamic convolution and attention mechanism into the multilayer perceptual machine model, and constructs the multilayer perceptual machine color emotion recognition model. The color features in animated movies are analyzed in terms of the viewer's emotions. The color and character suitability assessment model of animated films is established to explore the ability of animated films in color use and character design, as well as the viewers' perception of them.

II. Adaptive color perception machine model and emotion recognition model

II. A. Multi-Layer Perception Machine

Perceptron is a basic neural network model which consists of two layers of neurons and plays an important role in machine learning, it realizes the processing and transformation of input data through the combination of multiple neurons, and then transforms it through activation function to obtain the output result. The perceptron adjusts the weights according to the training data in order to get the best output, during the training process, the perceptron receives a sample and compares it with the output under the current weights, if the output does not match with the expectation, the weights are adjusted in order to expect a better output result. Each neuron receives multiple input values and sums them according to their weights to obtain a weighted sum. Next, it is nonlinearly transformed using an activation function and the transformed value is passed to the next layer of neurons.

The multilayer perceptron network model (MLP) is a powerful neural network model [17], [18], which is generalized from the perceptron model, and has more hidden layers than shallow neural networks, and therefore has more network parameters and a greater ability to handle nonlinear problems. The basic unit that constitutes a multilayer perceptual machine network is a neuron, whose mathematical expression is shown in equation (1), where w_i denotes the weight coefficients corresponding to the inputs x_i and b is the bias term:

$$z = \sum w_i x_i + b \tag{1}$$

A multilayer perceptron learns the appropriate parameter weights and bias terms from the input data through neurons, and uses the activation function $f(z)$ to transform linear relationships into nonlinear signals, enabling the network to accurately perform a variety of tasks in areas such as classification or regression prediction. These signals are eventually output from the input layer to the output layer through a series of hidden layers, and the layers are fully connected to each other.

The training process of a multilayer perceptron network consists of two stages: forward propagation and back propagation. The forward propagation algorithm computes the output of the next layer by computing the output of the previous layer until the output layer is computed. Assuming that the training data is (x_i, y_i), the total number of input layers is L, the weight matrices corresponding to all the implicit layers and the output layer is W, the offset vector is b, the output of each layer is calculated according to the rules of neural network arithmetic as a^l, the final output is a^L, and f is the activation function, z is the output after passing through the neuron, as in equation (2):

$$a^l = f(W^i a^{l-1} + b^l) \quad (2 \le l \le L) \tag{2}$$

In the process of forward propagation, the weight matrix W and the bias vector b of the network are randomly initialized, and a backpropagation algorithm is needed to determine the appropriate weight matrix W, with the bias vector b. The goal of the backpropagation algorithm is to find the optimal parameters by minimizing the loss function. The mean square error is a commonly used loss function in the backpropagation algorithm, which is used to measure the gap between the predicted and actual values output by the network. For each training sample (x, y), the coefficient 1/2 is used to offset the exponent derived from the differentiation, and its mean square error can be expressed as equation (3):

$$J(W,b,x,y) = \frac{1}{2} \| a^L - y \|_2^2 \tag{3}$$

Output to the last layer, i.e., the Lth layer, W and b of the output layer satisfy the following equation (4):

$$a^L = f(z^L) = f(W^L a^{L-1} + b^L) - y \|_2^2 \tag{4}$$

For the output layer parameters, the loss function becomes:

$$J(W,b,x,y) = \frac{1}{2} \| f(W^L a^{L-1} + b^L) - y \|_2^2 \tag{5}$$

In order to solve the gradient, the derivatives of W, b are obtained respectively, and the results are shown in Eqs. (6) and (7), where $\odot$ denotes the Hadamard product, i.e., the product of the corresponding elements of two matrices of the same dimension.

$$\frac{\delta J(W,b,x,y)}{\delta W^{L}}=\frac{\delta J(W,b,x,y)}{\delta z^{L}}\frac{\delta z^{L}}{\delta x}=(a^{L}-y)(a^{L-1})^{T}\odot f^{'}(z) \tag{6}$$

$$\frac{\delta J(W,b,x,y)}{\delta b^{L}}=\frac{\delta J(W,b,x,y)}{\delta z^{L}}\frac{\delta z^{L}}{\delta x}=(a^{L}-y)\odot f^{'}(z) \tag{7}$$

According to the forward propagation algorithm, we can obtain equation (8):

$$z^{l}=W^{l}a^{l-1}+b^{l} \tag{8}$$

In this way, we can derive the gradient of W^{l}, b^{l} for the l th layer as shown in Eqs. (9) and (10), where T denotes the transpose of the matrix:

$$\frac{\delta J(W,b,x,y)}{\delta W^{L}}=\frac{\delta J(W,b,x,y)}{\delta z^{L}}\frac{\delta z^{L}}{\delta x}=\delta^{l}(a^{l-1})^{T} \tag{9}$$

$$\frac{\delta J(W,b,x,y)}{\delta b^{L}}=\frac{\delta J(W,b,x,y)}{\delta z^{L}}\frac{\delta z^{L}}{\delta x}=\delta^{l} \tag{10}$$

Further, a recursive relational equation on δ is obtained as in equation (11):

$$\delta^{l}=\delta^{l+1}\frac{\delta z^{l+1}}{\delta z^{l}}=(W^{l+1})^{T}\delta^{l+1}\odot\sigma^{'}(z^{'}) \tag{11}$$

The recurrence relation equation for W,b can be derived from the recurrence relation equation for δ as in Eqs. (12) and (13):

$$W^{i}=W^{i}-a\sum_{i=1}^{m}\delta^{i,l}(a^{i,l-1})^{T} \tag{12}$$

$$b^{i}=b^{i}-a\sum_{i=1}^{m}\delta^{ij} \tag{13}$$

When the change values of both W and b are less than the iteration threshold, the linear coefficient matrix W and offset vector b of each hidden layer and output layer are output. At this point, the whole neural network training is completed.

II. B.Adaptive Color Perception Machine Model Construction

II. B. 1) Color Perception Machine

3D-LUT is a very effective image processing tool [19] that explicitly stores complex color mapping relationships in a lookup table, allowing input pixels to be quickly color corrected, and is widely used to enhance the perceived quality of digital images.

Given a 3D-LUT, its parameters can be expressed as $V\in\mathbb{R}^{M\times M\times M\times 3}$, where M is the number of intervals in which the pixel values are downsampled, which determines the accuracy of the 3D-LUT transformation. In practice, M is often set to 33 based on empirical values.3D-LUT performs color transformation efficiently by lookup and trilinear interpolation. The input pixel $p=\{r,g,b\}$, and the whole process can be expressed as:

$$p^{'}=LUT(p,V) \tag{14}$$

where $p^{'}$ is the output pixel, and $LUT(\cdot)$ represents the color transformation operation of 3D-LUT. Inspired by the principle of 3D-LUT, this chapter adopts a multilayer perceptron to model the complex color mapping relationship with fewer parameters, named color perceptron (ColorMLP). The ColorMLP model has two hidden layers, each containing N neurons. According to the principle of multilayer perceptual machine, the parameters (weights and biases) of ColorMLP can be represented as vectors $\Theta\in\mathbb{R}^{D}$, where $D=N^{2}+8N+3$. Then the color transformation process of ColorMLP can be expressed as:

$$p^{'}=ColorMLP(p,\Theta) \tag{15}$$

Compared to 3D-LUT, ColorMLP has more powerful nonlinear characterization capabilities.

II. B. 2) Adaptive color perception machine model

Based on the excellent properties of ColorMLP, this subsection proposes an adaptive color perceptron model AdaCM to achieve general photorealistic style transfer. AdaCM accepts the content map I_c and any style map I_s as inputs, firstly, the corresponding low-resolution $\overline{I}_c$ and $\overline{I}_s$ are obtained by downsampling, and then the parameter prediction module (PPM) combines the characteristic statistics of $\overline{I}_c$ and $\overline{I}_s$ to predict the parameters of Color MLP Θ, and finally the color manipulation module (CMM) performs a color transformation on the original input I_c according to Θ, and obtains a photorealistic stylized result I_{cs}.

(1) Parameter Prediction Module

The parameter prediction module establishes the color mapping relationship between content images and style images by predicting the parameters of ColorMLP, which centers on matching the statistics of content features and style features. The features of the input images are first extracted with the pre-trained VGG-19 at four scales (Conv1_1, Conv2_1, Conv3_1 and Conv4_1). The AdaIN-aligned features are then fused at multiple granularities using a series of Style-based Splatting modules, which consists of a weight-sharing convolutional layer with a step size of 2 to learn the joint distribution of style and content features, and a convolutional layer with a step size of 1 to fuse the currently learned features after AdaIN alignment. AdaIN alignment of the currently learned features and the features extracted by the pre-trained network. Finally, a two-way branch is used to extract local context information and global scene information, which are sufficiently combined and then predicted by the fully connected layer to obtain the parameters of ColorMLP Θ.

The whole process of the parameter prediction module can be expressed as:

$$\Theta = PPM(\overline{I}_c, \overline{I}_s) \tag{16}$$

Because PPM is processing the low resolution image after downsampling the original input, it does not consume much computational resources.

(2) Color Manipulation Module

The color manipulation module is mainly composed of ColorMLP, which performs color transformation on the input content map I_c according to the parameters Θ output from the parameter prediction module. Two inference methods are designed in the color manipulation module: direct color transformation and fast color transformation. Direct color transformation refers to stylizing the pixel-by-pixel of the input content map directly with ColorMLP. However, as the resolution grows, the amount of pixels in the picture increases dramatically. 3D-LUT, on the other hand, basically does not require floating-point arithmetic operations in processing the input pixels, and has a time complexity of $O(1)$, so it can perform fast operations even for high-resolution images. It is with the help of 3D-LUT that the fast color transformation substantially improves the efficiency of model inference. Firstly, ColorMLP is used to generate the parameter V_G of the 3D-LUT that is equivalent to the current style map:

$$V_G = ColorMLP(V_I, \Theta) \tag{17}$$

where V_I is the parameter of the constant 3D-LUT. The constant 3D-LUT is the 3D-LUT obtained by mapping each point to itself after sampling uniformly over the value range of the pixel.With the equivalent 3D-LUT, a fast style transformation can be performed according to Eq. (14):

$$I_{cs} = LUT(I_c, V_G) \tag{18}$$

The mapping relationships between colors can be visualized by generating an equivalent 3D-LUT of the style map.

(3) Regularization

This subsection proposes two regularization losses, pixel domain and spatial domain, to ensure that ColorMLP can generate continuous and smooth color mapping relations.

Considering the pixel domain first, this subsection designs the total variation loss (TV Loss) R_{lut} on the 3D-LUT space to penalize the differences between neighboring cells of the generated 3D-LUT. The equivalent 3D-LUT V_G of the current style map can be obtained according to Eq. (17), noting that $v=(i,j,k)$ is a point in V_G, and $V_G(v)$ is its corresponding color, R_{lut} can be computed by the following equation:

$$\mathrm{R}_{lut} = \sum_{v \in V_G} \sum_{v_n \in \Omega_{lut}} \| V_G(v) - V_G(v_n) \|_2^2 \tag{19}$$

where $\Omega_l ut = \{(i+1, j, k), (i, j+1, k), (i, j, k+1)\}$ represents the neighborhood of v in the 3D-LUT. The R_{lut} makes the artifacts in the image much reduced, but they are still present in some scenes. The main reason is that R_{lut} smoothes the local mapping relations around all the colors in the color space, whereas usually the color distribution of a content image is concentrated only in a certain region of the color space. Therefore, a regular TVLoss R_{img} is applied to the stylized image I_{cs} in the spatial domain, focusing on de-smoothing the local mapping relations of the colors appearing in the content map rather than all colors. Remembering that $p=(r,g,b)$ is a point in I_{cs}, R_{img} can be expressed as:

$$\mathrm{R}_{img} = \sum_{p \in I_{cs}} \sum_{p_n \in \Omega_{img}} \| p_n - p \|_2^2 \tag{20}$$

where $\Omega_{img} = \{(i+1, j), (i, j+1)\}$ represents the neighborhood of p in image space. The final total regular term is:

$$\mathrm{R}_{all} = \mathrm{R}_{lut} + \mathrm{R}_{img} \tag{21}$$

II. B. 3) Optimization algorithms

For training, content loss, mean and variance based style loss and regularization loss were used (Eq. 21). The final loss function is:

$$\mathrm{L} = \lambda_{sty}\mathrm{L}_{sty} + \lambda_{cont}\mathrm{L}_{cont} + \lambda_{\mathrm{R}}\mathrm{R}_{all} \tag{22}$$

where λ represents the weight of each loss term, which is taken as 1, 10, and 1000 in turn for the actual training. The resolution of the stylized map-equivalent 3D-LUT is set to 33 when calculating the regularization in the pixel domain.

II. C. Color Emotion Recognition Model for Multilayer Perceptual Machines

II. C. 1) Lexical metathesis

Lexical metathesis aims to take the input text or image data and slice it into substrings or sub-chunks to facilitate the learning of embedding representations and subsequent modeling. Specifically, the proposed model directly transforms the input image S into a feature map Z using a convolution kernel of size 7×7 and step size 2 with the following expression:

$$Z(c,i,j) = \sum_{k=1}^{c_m} \sum_{m=1}^{7} \sum_{n=1}^{7} S(k, 2i+m-1, 2j+n-1) \times U(c,k,m,n) \tag{23}$$

where $S(k, 2i+m-1, 2j+n-1)$ denotes the pixel value of the position $(2i+m-1, 2j+n-1)$ on the kth channel of the input feature map, $Z(c,i,j)$ is the pixel value of the position (i,j) on the c th channel of the output feature map, and $U(c,k,m,n)$ is the weight of the convolution kernel on the c output channel and (m,n) the weight of the position (m,n) on the k input channel, and when $(2i+m-1, 2j+n-1)$ is out of the range of the input feature maps, a 0-value padding is used. This method effectively converts the input image into a feature map to be further processed by the deep learning model.

II. C. 2) Multilayer Perceptron with Dynamic Convolution and Attention Mechanisms

The proposed dynamic convolution focuses on time and frequency direction feature capture. The color mood features are effectively identified in different directions by deep convolution, and the separation of attention mechanism dynamically focuses on key regions to enhance the model's recognition of subtle features (e.g., pitch change). Combining the attention mechanism with the convolution operation to enhance the feature extraction effect. Four deep convolutional layers, two focusing on anisotropic features in the horizontal and vertical directions, and the other two focusing on capturing local features. For the input feature map Z, the four sets of convolution kernels compute features in different directions with the following expression:

$$\begin{aligned} V_1 &= DWConv_{3\times1}(Z) \\ V_2 &= DWConv_{1\times3}(Z) \\ V_3 &= DWConv_{3\times3}(Z) \\ V_4 &= DWConv_{3\times3}(Z) \end{aligned} \tag{24}$$

where V_i is the output feature map, $i=1,2,3,4$. This deep convolution approach helps the model to capture the spatial information finely. An attention mechanism is attached after each deep convolution and generates a weight map through a convolutional layer and an adaptive average pooling layer AvgPool(·), modulated by a Sigmoid activation function. Let the feature V_i be denoted as $V_i=[V_i(1);V_i(2);\cdots;V_i(C)]$, and C is the number of channels of the feature. The computational expression for the attention mechanism is as follows:

$$\begin{aligned}\hat{V}_1(j)&=sigmoid(AvgPool(DWConv_{1\times5}(Z))(j))V_1(j)\\ \hat{V}_2(j)&=sigmoid(AvgPool(DWConv_{5\times1}(Z))(j))V_2(j)\\ \hat{V}_3(j)&=sigmoid(AvgPool(DWConv_{1\times5}(Z))(j))V_3(j)\\ \hat{V}_4(j)&=sigmoid(AvgPool(DWConv_{5\times1}(Z))(j))V_4(j)\end{aligned} \tag{25}$$

where $AvgPool(DWConv_{Kb}\times K_w(Z))(j), j=1,2,\cdots,C$ means that the loser Z first performs a deep convolution $DWConv_{K_h\times K_w}(\cdot)$ operation, and then averages the convolution results, Finally, the data of the j channel in the average pooling result are extracted, and the weights about the specific channels are generated through Sigmoid for the subsequent attention mechanism. The convolutional layer output is multiplied by the corresponding weight map to achieve attention weighting of the output. The final feature map can be expressed as $\hat{V}=[\hat{V}_1;\hat{V}_2;\hat{V}_3;\hat{V}_4]$, where $\hat{V}_i=[\hat{V}_i(1);\hat{V}_i(2);\cdots;\hat{V}_i(C)]$. This mechanism allows the model to give different weights to features according to their importance, thereby highlighting key features and improving the sensitivity and accuracy of the model.

Dynamic convolution flexibly adapts to the importance of different features through its unique structure and dynamic weighting mechanism, effectively capturing complex speech signal features more efficiently than traditional convolutional layers. This approach improves the efficiency of feature extraction and enhances the accuracy of the model in handling complex spatially structured data. Dynamic convolution has great potential for application in color mood recognition and is especially suitable for highly fine-grained recognition scenarios. By combining the spatial feature extraction capability of traditional convolutional networks with the dynamic weighting of the attention mechanism, dynamic convolution can process color spectrograms more efficiently and identify complex spatial patterns associated with emotional states, bringing significant advantages to highly sensitive emotion recognition tasks.

II. C. 3) Separable attention mechanisms

Inspired by the ResNest model, a novel separable attention is proposed with the aim of segmenting the input feature map in the channel direction and applying spatial attention on each segment. This approach can effectively improve the model's ability to process multidimensional data, especially when dealing with images with rich channel information.

The generation of the attention map is realized by a specially designed convolutional layer [20], which converts the input feature map into an attention map with four output channels Q with the following expression:

$$Q=softmax(Conv_{3\times3}(\hat{V})) \tag{26}$$

where the attention map $Q=[Q_1;Q_2;Q_3;Q_4]$ is normalized by Softmax to make the sum of attention values on each pixel point to be 1, which ensures the reasonableness and validity of the attention distribution. By multiplying each attention map $Q_i(i=1,2,3,4)$ with the same dimension as the feature map $\hat{V}_i$ on the channel, denoted as Q_i, the dynamic weighting of the features is achieved by multiplying the features of each part with its corresponding attention map.

In summary, dynamic convolution demonstrates significant advantages in enhancing the feature processing capability of the model through its unique attention generation and feature weighting mechanisms. This makes it particularly suitable for complex image processing tasks that require careful analysis of channel information.

III. Role fit assessment model

In the era of market segmentation, a certain product can only satisfy a particular consumer class, which requires that the product characteristics are consistent with the personality of the target consumer group. If the product is contrary to consumer expectations, it will cause consumer misunderstanding. As a cultural consumer product, animated movies also need to pay attention to their character suitability. This study adopts the Delphi method to study the appropriateness of color and character from the perspective of animated films.

III. A. The Delphi Method

The Delphi method was firstly created by RAND Corporation in the late century [21], firstly used in science and technology forecasting, and then widely used in market forecasting since the 1960s. The Delphi method refers to the use of correspondence to solicit the opinions of experts, and after several rounds of solicitation, the prediction opinions tend to be centralized. It overcomes the disadvantages of the meeting in which the experts can not fully express their opinions and the opinions of authority figures influence the opinions of others, and the experts can fully express their own opinions.

Delphi method of prediction generally take the following steps:

(1) Determine the prediction topic and select experts. Selected experts must be determined to predict the object of a person with extensive knowledge, so that the object of the prediction to provide credible opinions. The number of experts is generally 10 to 20.

(2) Design the consultation questionnaire and prepare the relevant materials. Will predict the object of the survey project, in order to make the consultation form, while filling out the requirements, instructions and design, so that experts can make predictions in accordance with the unified requirements.

(3) Multiple rounds of consultation are conducted in an anonymous manner. The first round of consultation forms and descriptive information is issued, and the experts are asked to answer one by one and give their personal preliminary opinions. After the forms are recovered, they are statistically analyzed and opinions are summarized. Processing methods can be selected from the weight of the number of people method, peak method, mean method or quartile method.

The opinions summarized and collated in the first round are fed back to the experts for a second round of advice. After receiving the second round of information, the experts can understand the opinions of other experts and make a judgment on this, and he can modify his own opinions or adhere to his first round of opinions.

Depending on the degree of consistency of the feedback, a third round and more multiple rounds of consultation may be conducted.

(4) For a very small number of heterodox opinion cases for thematic contact, in-depth consultation, to determine the results of the consultation.

The consultation process can generally be concluded through one round, and the use of computerized communication instead of written communication can speed up the consultation process.

III. B. Construction of evaluation index system for character suitability of animated movies

This paper constructs the evaluation index system of color and character suitability of animated films as shown in Table 1.

Table 1: Evaluation index system on adaptation of colors and roles in animated films

Target layer	Primary index	Secondary index
Adaptation of colors and roles in animated films	Role expression mechanism in color system (A)	Role appearance expression in color narrative (A1)
		Role personality expression in color narrative (A2)
		Role psychological expression in color narrative (A3)
		Role worldview construction in color narrative (A4)
	Role emotional feature in color system (B)	Role subjective emotion (B1)
		Role life experience (B2)
		Role dramatic growth (B3)
		Role future prediction (B4)
	Role environment in color system (C)	Role emotion environment (C1)
		Role story environment (C2)
		Role growing environment (C3)
		Role living environment (C4)
	Integration of color and role emotion (D)	Color visual emotion (D1)
		Color creation of emotional atmosphere (D2)
		Role color configuration (D3)
		Role color texture (D4)

III. C. Methodology for determining indicator weights

III. C. 1) Methodology for determining weights

Weighting is a quantitative form of comparison, weighing the relative importance of the factors in the overall thing being evaluated. When a number of indicators are used for comprehensive evaluation, the role of each indicator on the evaluation object is not equally important. In order to reflect the degree of importance of each evaluation indicator in the evaluation system, we must assign different weight coefficients to each indicator.

There are many ways to determine the weights, the commonly used methods to solve the weights are, the direct composition of the weight method, set value iteration method, entropy value method, etc. Statistical methods to determine the weights of the inverse of the variance of the weight method, the weighted average method, the coefficient of variation of the weight method, the optimal weight method, etc., as well as hierarchical analysis, fuzzy synthesis judgment method, gray correlation method, etc..

The role of weights is to highlight the role of key objectives and indicators in multi-objective decision-making and multi-indicator evaluation, so that multi-objectives and multi-indicators can be reasonably structured and optimized to achieve the overall optimal and satisfactory combination. The realization of the role of weighting depends on the rating value of the evaluation indicators. The evaluation result of each indicator is the product of its weight and its rating value. The reasonableness or otherwise of the weights directly affects the reasonableness and authenticity of the evaluation results. Moreover, as the weights of each evaluation index constrain each other the sum of the weights of a group of associated evaluation indexes is equal to, the irrationality of the weights of a certain evaluation index will definitely affect the rationality of the weights of the other interrelated indexes, thus affecting the overall evaluation results.

In this study, the inverse variance weight method is used to carry out the research on the weights of color and character fit elements. The inverse of the variance is used as the weight to synthesize various observations, and the effect is that the variance is minimized, i.e., the error in the weight value obtained is minimized. The evaluation function is as follows:

$$W_i = \frac{S_i^{-2}}{\sum_{i=1}^{n} S_i^{-2}} \quad i = 1,2,3,...,n \tag{27}$$

Among them:

$$S_i^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2 \quad i = 1,2,3,...,n \tag{28}$$

Weights are to be divided into weights from a number of evaluation indicators, a set of evaluation indicator system corresponding to the weights constitute a weighting system. A set of weight system $\{W_i \mid i = 1,2,....,n\}$, must satisfy the following two conditions: the weight value of each indicator should be in the range of 0~1; the sum of the weight values of the n indicators is 1. If the evaluation indicators of the evaluation system are two levels, then $\{W_{ij} \mid i = 1,2,....,m;\ j = 1,2,...,n\}$ sums to 1.

III. C. 2) System of weighting indicators

According to the above weighting theory, this study establishes a two-level weighting research index system for character suitability in animated movies.

(1) First-level index system C_i

In this study, the category of fitness elements is designated as a first-level indicator $\{C_i \mid i = 1,2,\ldots,n\}$, and its corresponding weight $\{W_{C_i} \mid i = 1,2,...,m\}$, where m is equal to 3, is the number of fitness element categories.

The weights of the first level indicators

$$w_{c_i} = \frac{S_i^{-2}}{\sum_{i=1}^{m} S_i^{-2}} \quad i = 1,2,...,m \tag{29}$$

(2) Secondary indicator system C_{ij}

In this study, each fitness element is designated as a secondary indicator $\{C_{ij} \mid i = 1,2,....,m,\ j = 01,02,...,k\}$, whose corresponding weights are $\{Wc_{ij} \mid i = 1,2,...,n,\ j = 01,02,...,n\}$, where n is the total number of fitness elements in the corresponding category.

Weights of secondary indicators:

$$Wc_i j = \frac{S_{ij}^{-2}}{\sum_{i=1}^{m}\sum_{j=0l}^{n} S_{ij}^{-2}} \quad i = 1,2,...,m; j = 01,02,...,n \tag{30}$$

Combined weights of secondary indicators:

$$W_{ij} = \sum_{i=1}^{m}\sum_{j=01}^{n} Wc_i Wc_{ij} = 1 \tag{31}$$

IV. Analysis of Color Emotion and Character Adaptation in Animated Films

IV. A. Color Emotion Analysis

Using the adaptive color perception machine model and emotion recognition model in this paper to extract, perceive and recognize the picture color of eight animated movies, including Finding Dreams, Crazy Animal City, Flying House, Robot Story, A Thousand and One Searches, Your Name, Journey to the West, and Ne Zha's Magic Boy Haunts the Sea, and the overall dimensional multiple correspondences analysis is shown in Figure 1.

From the overall viewpoint, the scatter distribution of each visual feature between the neutral picture emotion and the positive picture emotion is close and closely connected, but there is a significant difference between the two and the negative picture emotion. It can be found that the scatters of neutral tone, warm tone and high brightness are distributed near the scatters of neutral and positive emotion, and the scatters of low brightness and cold tone are distributed near the scatters of negative emotion, and it can be considered that there is a certain connection between them, and that warmth, coldness, and brightness are one of the important linguistic symbols of animated movie picture, which will directly affect the visual feeling and emotional experience of the viewers, and the results of the data analysis show that the warm tone, high brightness The results of data analysis show that warm color tone and high brightness movie screen has strong visual impact, full of vitality and vigor, with high emotional arousal, easy to stimulate the positive emotions of the viewers, while cold color tone and low brightness movie screen does not conform to the visual perception of the viewers, and is easy to cause negative emotional experience to the viewers.

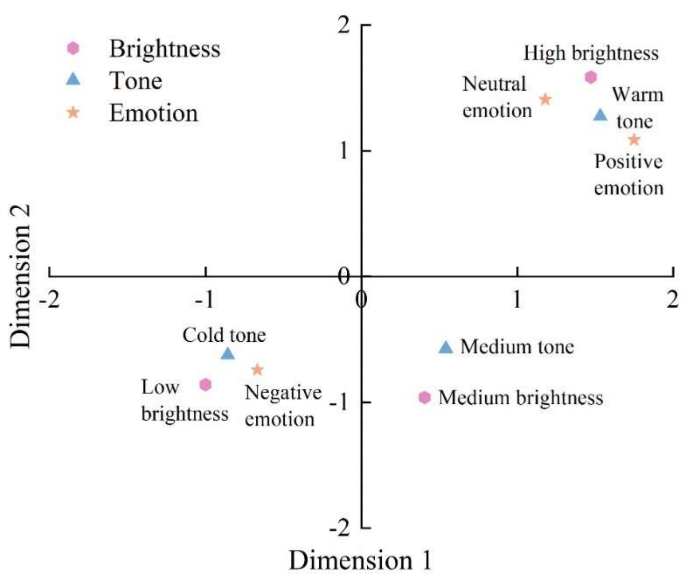

Figure 1: The overall dimension multiple correspondence analysis

The color dimension multiple correspondence analysis is shown in Figure 2. From an overall point of view, the neutral, positive and negative emotion scatters are distributed farther from each other, indicating that there are more obvious differences between the three in terms of the main color and the number of colors, and it can be found that the yellow and orange scatters are distributed near the neutral emotion scatters, the red, green, blue, and violet scatters are distributed near the positivity emotion scatters, and the black and white scatters are distributed near the negativity emotion, which can be regarded as there is a certain connection between them, and in addition, when the number of colors is too little In addition, when the number of colors is too few or too many (less than 3 or more than 10), the emotion of the screen often tends to be negative. The dominant color determines the emotional tone of the movie screen, and is one of the most intuitive visual features of the movie screen, which can directly affect the visual feeling of the viewer and stimulate the viewer's emotional response. From the results of data analysis, it can be found that red, green, blue and purple tones have strong color tension in the movie screen, which can evoke a sense of aesthetic pleasure in the viewers. The color expression of black and white tone movie screen is weak, which is closely associated with negative emotions. In addition, the animation movie screen color matching should be harmonious and unified, the application of less color screen more boring, boring. More color application of the screen is easy to busy, complex, but also aggravate the cognitive burden of the viewer, animation film makers should consciously control the number of colors and combinations of the movie screen, the reasonable collocation and use of color, to give the viewer to the beauty of harmony, to avoid the color complexity caused by the viewer's visual fatigue, the pursuit of the movie screen as a whole color hierarchy, to give the viewer a diversified emotional feeling.

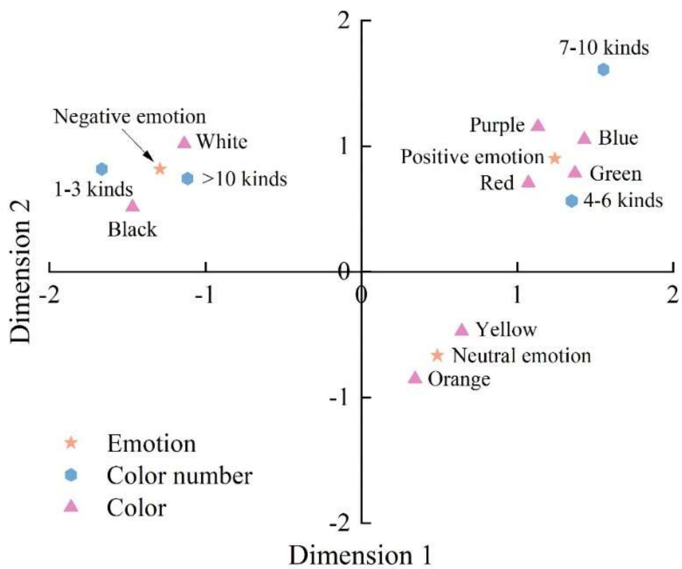

Figure 2: Color dimensional multiple correspondence analysis

Table 2: Evaluation index weight on adaptation of colors and roles in animated films

Target layer	Primary index	Weight	Secondary index	Weight
Adaptation of colors and roles in animated films	Role expression mechanism in color system (A)	0.2689	A1	0.2705
			A2	0.2523
			A3	0.2364
			A4	0.2408
	Role emotional feature in color system (B)	0.2537	B1	0.2625
			B2	0.2475
			B3	0.2411
			B4	0.2489
	Role environment in color system (C)	0.2365	C1	0.2669
			C2	0.2465
			C3	0.2521
			C4	0.2345
	Integration of color and role emotion (D)	0.2409	D1	0.2327
			D2	0.2443
			D3	0.2739
			D4	0.2491

IV. B. Evaluation of role fit

IV. B. 1) Calculation and analysis of indicator weights

According to the constructed evaluation index system of the suitability of color and character in animated films, weight calculation is carried out, and the weights of each index are obtained as shown in Table 2, and the weights of the first-level indexes are sorted from the largest to the smallest as the mechanism of the character expression in the color system (A), the emotional characteristics of the character in the color system (B), the fusion of the color and the character's emotion (D), and the environment of the character in the color system (C), with the weights being respectively 0.2689, 0.2537, 0.2409, and 0.2365.

IV. B. 2) Analysis of evaluation results

According to the evaluation index system of the adaptability of color and character of animated films, the questionnaire was designed, and the five-level Likert scale was used as the calculation tool, and 1~5 indicated "very dissatisfied", "dissatisfied", "average", "satisfied" and "very satisfied".

The author takes the animated movie “Journey to Dreamland” as the research object, and distributes 1,000 network questionnaires to the moviegoers who have seen this animated movie, and 954 questionnaires are recovered, with a recovery rate of 95.4%, among which 910 questionnaires are valid, with an effective rate of 91%. The results of the valid questionnaires are processed and analyzed, and the final results are calculated according to the index weights of the animated film color and character suitability evaluation index system, and the results of the animated film color and character suitability evaluation can be obtained as shown in Table 3.

From the results in Table 3, it can be seen that the animated film “Journey to the Dream” scores 4.17 points in the overall score of color and character suitability, and moviegoers are more satisfied with the color and character suitability of the animated film. In the first-level indicators, the scores in descending order are: the integration of color and character emotion (4.26), the character's emotional characteristics in the color system (4.20), the character's expression mechanism in the color system (4.15), and the character's environment in the color system (4.07), all of which are in the midst of 4 points. The scores of the tertiary indicators ranged from 3.91 to 4.44, and the highest scoring tertiary indicators were character appearance expression in color narrative, color visual emotion, and the lowest scoring tertiary indicator was character psychological expression in secant narrative.

Table 3: Evaluation results on adaptation of colors and roles in animated films

Target layer	Primary index	Weight	Secondary index	Weight
Adaptation of colors and roles in animated films (4.17)	Role expression mechanism in color system (A)	4.15	A1	4.44
			A2	4.14
			A3	3.91
			A4	4.09
	Role emotional feature in color system (B)	4.20	B1	4.42
			B2	4.09
			B3	4.22
			B4	4.06
	Role environment in color system (C)	4.07	C1	4.03
			C2	3.92
			C3	4.37
			C4	3.96
	Integration of color and role emotion (D)	4.26	D1	4.44
			D2	4.42
			D3	4.02
			D4	4.19

V. Conclusion

The article constructs animated movie color emotion recognition model based on multilayer perceptual machine model. In order to explore the fitness of animated movie color and character, the character fitness assessment model is constructed. After analyzing the color emotion of animated movies, the color character suitability of an animated movie is evaluated.

(1) Neutral tone, warm tone, and high brightness scatters are distributed near the neutral and positive emotion scatters, and low brightness and cold tone scatters are distributed around the negative emotion scatters. Warm-toned, high-brightness movie images are easy to stimulate positive emotions, while cold-toned, low-brightness movie images have a more obvious effect on negative emotional experiences.

(2) Yellow and orange are closer to neutral emotions, red, green, blue and purple are distributed around positive emotions, and black and white are connected to negative emotions. When the number of colors is too few (<3) or too many (>10), the picture emotions are often directed to negative emotions. Red, green, blue and violet colors are more likely to be able to stimulate pleasure. Black and white tones often make people feel negative emotions.

(3) The color and character appropriateness score of the animated film “Finding Dreams” is 4.17, which is a good evaluation result. Its first-level index score is between [4.07, 4.26], and its third-level index score is between [3.91, 4.44]. The viewers' satisfaction with the color and character adaptation of this animated film is high.

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