Application of Style Transfer Algorithm in the Design of Animation Pattern Special Effect

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Abstract. In recent years, the in-depth study and rapid development of computer vision technology has become an important aspect of image style transfer technology. Use the style transfer algorithm to complete the conversion of the artistic style of the image, and use computer tools to automatically convert the style of other images to the input image, so that the two styles are exactly the same, but the original image will remain unchanged, and this style will be overwritten in other images. In order to complete the reconstruction process, while protecting the original content of the image, there are other style transfer algorithms for visual effects. Computer vision, film and television production and other fields play an unusual role. The style transfer algorithm transfers the painting elements to the movie, and produces a unique animation special effect art effect, thereby providing new ideas and situations for the animation pattern special effect design of the artificial intelligence pattern style transfer algorithm. Therefore, exploring the theoretical approach of pattern style transfer algorithm and improving the diversity of pattern style transfer has greater trade value and industrial application value. Based on the deep learning theory, this paper describes the training model and deep learning framework of the convolutional neural network model VGG19, and introduces the basic technology in the application process in detail, and then applies the animation pattern special effect style transfer algorithm. Summarize the advantages of the style transfer algorithm in the design of animation pattern special effects.

Key words: Artificial intelligence, Style transfer, Animation pattern special effect design, Design practice

1. Introduction

Animated patterns with special effects can be seen everywhere in life, including TV commercials, movies, animations, etc. Special effect animation patterns are usually used to attract people's attention to the content represented by the patterns. The design of traditional animation pattern special effects is generally carried out in the manual design process, which requires a lot of manpower and resources [1].
In addition, artificially designed animation effects have a shortcoming, which cannot be transferred to other types of animation in a specific animation style [2]. Image style transfer algorithm based on computer technology is the current research hotspot of image style transfer. Image style transfer is widely used in real life. Image style transfer algorithm can be transferred to photos with special effects. Therefore, ordinary photos can use the style transfer algorithm technology to transfer the photo style with the artist's style to the ordinary photos to become new images. It can also realize two different styles according to actual needs, and realize the fusion creation of styles, etc. [3]. Therefore, with the help of computer science and technology, the realization of animation style transfer design has gradually become a hot topic in the field of image style transfer [4].

The essence of image style communication is to maintain the basic meaning of specific image content. The style expression extracted from images of different styles is applied to the original image, and the purpose of image style expression and the image style are agreed upon [5]. The image style transfer method can be summarized as two types of improving and expanding the two style transmission methods, transferring the artistic style and neural style of images. Among them, the method of transferring neural style has received a lot of attention. An image style transmission method based on integrated neural network. This method uses an integrated neural network to synthesize textures, and integrates the style of the input style image and the content of the input style image [6]. The second multifunctional synthesis method based on the integrated neural network first uses histogram loss to solve the unstable synthetic texture problem. In addition, in the multifunctional framework, a method to integrate the style loss of style transfer objects is also proposed [7]. This loss can improve the separation ratio of content and style, making the visual effect of the transmitted image more natural.

With the development of artificial intelligence in recent years, the image style transfer algorithm learning technology has achieved phased results. The image style transfer algorithm has important theoretical research value and potential commercial application value. It is important for artistic creation and design, pictures and videos. Edit processing, information hiding, etc. play a huge role [8]. The use of style transfer algorithms in the design of animation pattern special effects plays a very important role in stimulating human thinking about images, improving work efficiency, and making images more realistic and vivid [9]. Style transfer algorithm is a fusion of classical art form and artificial intelligence technology, which has a great influence on the field of art and technology. Not only that, products with style transfer algorithm technology as the core have attracted many users in a short period of time, which proves the wide application market [10].

2. Algorithm establishment

2.1. Style transfer algorithm
Mark the original image and the generated image as the sum, using the sum, reference, and characteristic response of each level, the error square loss function between the two can be defined as the following.

\[ L_{\text{content}}(\hat{p}, \hat{x}, l) = \frac{1}{2} \sum_{ij} (F^l_{ij} - P^l_{ij}) \]  

\[(1)\]

The loss function derives the activation value of the lth layer:

\[ \delta L_{\text{content}} \delta F^l_{ij} = \begin{cases} (F^l - P^l)_{ij}, & \text{if } F^l_{ij} > 0 \\ 0, & \text{if } F^l_{ij} < 0 \end{cases} \]  

\[(2)\]

Use the back propagation algorithm to calculate the slope of \( \hat{x} \) and change the value of the white noise map \( \hat{x} \) to obtain a result similar to the original image. The style expression is set in the responses of all levels of the integrated neural network, and the relationship between the responses of different filters is calculated. The relationship between these functions is defined by the Gram matrix:
The inner product of feature map vectorization:

\[ G_i^l = \sum_k F_i^l F_i^{l'} \]  

(4)

The original image \( \hat{a} \) and white noise image \( \hat{x} \), respectively calculate the Gram matrix \( A_l \) and \( G_l \) of the l layer, the loss function of this layer is:

\[ E_l = \frac{1}{4N_l^2M_l^2} \sum_{i,j} (G_l^i - A_l^i)^2 \]  

(5)

The total loss function is:

\[ L_{\text{style}}(\hat{a}, \hat{x}) = \sum_l \omega_l E_l \]  

(6)

Where \( \omega_l \) is the weight of layer l, and the derivative of \( E_l \) with respect to the activation value of layer l is:

\[ \frac{\delta E_l}{\delta F_{ij}^l} = \begin{cases} \frac{1}{N_l^2M_l^2} \left( (F_i^l)^T (G_l^i - A_l^i) \right)_{ij}, & \text{if } F_{ij}^l > 0 \\ 0, & \text{if } F_{ij}^l < 0 \end{cases} \]  

(7)

The final loss function form is:

\[ L_{\text{total}}(\hat{p}, \hat{a}, \hat{x}) = \alpha L_{\text{content}}(\hat{p}, \hat{x}) + \beta L_{\text{style}}(\hat{a}, \hat{x}) \]  

(8)

2.2. Improved style transfer algorithm framework

The pre-trained VGG19 model is used for feature extraction, and weight values are assigned according to content loss and style loss. The total loss function is as shown in equation (9):

\[ L_{\text{total}}(\hat{c}, \hat{s}, \hat{x}) = \alpha \sum_l \omega_{lc} L_{\text{content}}(\hat{c}, \hat{x}, l) + \beta \sum_l \omega_{ls} L_{\text{style}}(\hat{s}, \hat{x}, l) \]  

(9)

In the formula: \( \omega_{lc}, \omega_{ls} \) is the respective loss weight of the content image \( \hat{c} \) and style image \( \hat{s} \) in the first layer; \( \alpha \) and \( \beta \) are hyperparameters that balance the two losses. Taking the total loss as the optimization goal, the gradient descent method is used to obtain the generated map, and finally the color transfer algorithm is used to correct the color distortion generated map.

2.3. Loss function

(1) Content loss function. Suppose the response of a certain layer is \( F_i^l \in R^{N_l \times M_l} \), where \( N_l \) is the number of filters in the l layer, \( M_l \) is the size of the filters in the l layer, \( F_{ij}^l \) is the output of the i-th filter in the l layer at position j, and \( \hat{p} \) is Provide Content image, \( \hat{x} \) represents the generated image, \( F_i^l \) and \( F_i^{l'} \) respectively represent the response of the two to the l layer, so the calculation formula of the content loss of the l layer is as follows:

\[ L_{\text{content}}(\hat{p}, \hat{x}, l) = \frac{1}{Z} \sum_{l,j} (F_{ij}^l - P_{ij}^l)^2 \]  

(10)

(2) Style loss function. \( G_i^l \in R^{N_l \times M_l}, \hat{a} \) indicate the image that provides style, \( \hat{x} \) indicates the generated image, \( A_l^i \) and \( G_l^i \) respectively indicate the response of the two to the l layer, so the calculation formula of the style loss of the l layer is as follows:

\[ E_l = \frac{1}{4N_l^2M_l^2} \sum_{i,j} (G_{ij}^i - A_{ij}^l)^2 \]  

\[ L_{\text{style}}(\hat{a}, \hat{x}) = \sum_{l=0}^L \omega_l E_l \]  

(12)

3. Modeling method

3.1. Convolutional Neural Network Model

There are 16 integrated layers and 3 fully connected layers in the convolutional neural network model
VGG. In addition, the VGG network has up to 5 interaction layers distributed under different interaction layers.

Volume base level: Each Nulun uses local correlation as a filter, local data is integrated in a window sliding manner, and a weight sharing mechanism is used to extract characteristics of filter values.

Pooling layer: Most of it is sandwiched at the base layer of pooling volumes, generally sandwiched between average pooling, maximum pooling and probability pooling. The number of functional data used for compression and extraction.

Fully connected layer: In order to improve performance, the activation function of each nulun of the fully connected layer generally uses the ReLU function.

Structural similarity: In terms of brightness, contrast and structure, the overall reference image quality evaluation index for image similarity can be determined.

Mathematical formulas related to operations can be expressed as follows:

\[ l(X,Y) = \frac{2\mu_X\mu_Y+C_1}{\mu_X^2+\mu_Y^2+C_1} \] (13)

\[ c(X,Y) = \frac{2\sigma_X\sigma_Y+C_2}{\sigma_X^2+\sigma_Y^2+C_2} \] (14)

\[ s(X,Y) = \frac{\sigma_{XY}+C_3}{\sigma_X\sigma_Y+C_4} \] (15)

Among them, \( \mu_X, \mu_Y \) represents the mean value of image X and Y respectively; \( \sigma_X, \sigma_Y \) represent the variance of image X and Y respectively; \( \sigma_{XY} \) represents the covariance of image X and Y, namely:

\[ \mu_X = \frac{1}{H\times W} \sum_{i=1}^{H} \sum_{j=1}^{W} X(i,j) \] (16)

\[ \sigma_X^2 = \frac{1}{H\times W-1} \sum_{i=1}^{H} \sum_{j=1}^{W} (X(i,j) - \mu_X)^2 \] (17)

\[ \sigma_{XY} = \frac{1}{H\times W-1} \sum_{i=1}^{H} \sum_{j=1}^{W} ((X(i,j) - \mu_X)(Y(i,j) - \mu_Y)) \] (18)

Among them \( C_1, C_2, C_3 \) and are constants. In order to avoid the case where the denominator is 0, the price range of SSIM is [0,1]. The larger the value, the smaller the image distortion.

4. Evaluation results and research

In this experiment, Python language, Tensorflow, and Pytorch framework are selected to test the style transfer algorithm in the animation pattern special effect design test. For convolutional neural network models VGG16 and VGG19 training. Because the depth of the VGG network and the weight value of the network structure are very large, the model training is very slow, so the model used for research is the pre-trained model of the Image Net data set. In order to build the model used in the simulation, this study brought the media variables of the integration hierarchy from the pre-trained model. This parameter is constant, which means it is no longer trained and not used for the back propagation process. In addition, the fully connected layer of VGG will be discarded. The parameters are set in Table 1.

| Parameter item   | VGG16  | VGG19  |
|------------------|--------|--------|
| Training times   | 1000   | 1000   |
| Style loss weight| 1      | 1      |
| Content loss weight| 500   | 500    |
| L2 regularization coefficient | 0.005 | 0.005 |
| Probability of dropout | 0.5 | 0.5 |
|------------------------|-----|-----|
| Noise ratio            | 0.5 | 0.5 |
| Learning rate          | 10  | 10  |

In order to prove the validity of the experiment, 20 animation patterns were selected as the test set from the two open source DAIVS and FBMS datasets containing a total of 109 animation pattern sequences. All the image sizes were 256*256, which passed Johnson, Huang, The four methods of Anderson and the style transfer algorithm perform style conversion and record the running time. In Figure 1, these four methods are the average of the time required to convert 20 animation pattern data sets. It can be seen that the style transfer algorithm also has sufficient advantages in processing animation pattern special effect design operation speed.

![Figure 1. Time comparison of different methods for processing animation pattern special effects design](image1.png)

For the test set images in the data set, the CycleGAN algorithm, CycleGAN+ style encoder algorithm and style transfer algorithm are used for style transfer operations. The same image is randomly selected from the generated style transfer images, and the Brenner gradient function, Tenengrad gradient function, Laplacian gradient function, gray-level variance function, gray-level variance product function, variance function. Some experimental results of image special effects design are shown in Figure 2.

![Figure 2. Evaluation results of pattern special effects design](image2.png)
Figure 2 shows that using the same training set and test set, under the same experimental conditions, the style transfer image generated by CycleGAN+ style encoder is higher in the objective evaluation method than the style transfer image generated by CycleGAN, which proves that the style code is added to the CycleGAN method. The style transfer result generated by the editor is better. And the style transfer image generated by the image style transfer algorithm is higher than the other two algorithms in the objective evaluation method, which shows that the pattern special effect design using the style transfer algorithm is better than the pattern special effect design generated by the other two algorithms, which proves the segmentation transfer algorithm. The effectiveness and superiority of design special effects.

5. Conclusion

Through the integration of computer science and animation art, it can make up for the shortcomings of the original hand-painting, and at the same time can stimulate the new creativity of animation special effects design and obtain new results. The style transfer algorithm can quickly and effectively generate a variety of image styles, greatly improving efficiency, saving manpower and material resources, and creating unique and novel animation special effects designs. Provide strong technical support for animation production from an artistic perspective, and further expand the scope of animation special effects design. Instead of using pixel loss, it uses crustal loss to shorten image output time, and a new idea for image generation is proposed. The image style transfer algorithm can quickly generate a variety of images through a variety of effects, which can be applied to film post-processing, poster design, artistic creation, conceptual design, and so on. Transfer images with different artistic style attributes, and perform color correction on the transfer results. Experiments show that the implemented algorithm can obtain a more ideal animation pattern special effect design according to actual needs.

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