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Digital Image Art Style Transfer Based on Deep Short and Long Term Memory

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Abstract. *With the rise of artificial intelligence, deep learning techniques are increasingly being used in real-life applications, especially in image processing. People have started to use image processing techniques based on deep learning technology to accomplish the task of image art creation, and one of the more popular directions is image style transfer. The traditional image style transfer method is difficult to meet the requirements of practical applications in terms of visual effect, therefore, a digital image art style transfer method based on deep Long Short-Term Memory (LSTM) is proposed. Firstly, the spatial texture feature data is forgotten and filtered by weight through input gates, forgetting gates, output gates and storage elements, so as to selectively choose some data for cyclic iterative training. Secondly, the Whale Optimization Algorithm (WOA) is introduced to perform intelligent solution of the LSTM parameters, thus proposing the WOA-LSTM algorithm. Finally, the total variational regularization based on L2 parametrization is introduced in the image style transfer process to improve the spatial smoothness of the synthesized images. The experimental results show that the problem of significant content distortion in the generated images can be effectively improved by setting the WOA parameters reasonably. Compared with other style transfer algorithms, the average absolute value error (MAE) of the proposed WOA-LSTM algorithm is reduced by 6.5 %. The proposed method can effectively solve the problems of unnaturalness and scatter in the synthetic images and obtain better visual effects for the human eye.*
Keywords: Image style transfer; Artificial intelligence; LSTM; WOA; Total variable regularization;

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1. Introduction.

As artificial intelligence (AI) improves, whether in the domains of natural language processing, computer vision, or autonomous vehicles, deep learning techniques are increasingly being used in practical applications, notably in image processing.

In the era of the information boom [1,2], there is a greater expectation that AI will be able to carry out a variety of artistic jobs, and visual art style transfer is one of these applications.

Image style transfer is a common use of deep learning techniques [3,4]. In this process, a pair of photos is taught to have the texture, color, and luminance of the target image while maintaining the semantic content information from the original images. Style transfer therefore has many potential applications and high financial value in industries like beauty filters, filmmaking, and rendering animation [5,6]. The lack of significant information in the generated images, the unclear contours of the primary semantic content, and the presence of artifacts, among other issues, make the style transfer effect unsatisfactory and lead people to want to customize the effect of the generated images.

Artificial intelligence has grown in popularity among scientists thanks to the advent of deep learning [7,8]. Deep learning has recently shown remarkable achievements in the areas of autonomous cars, computer vision, and natural language processing. With the quick advancement of short video technology, people's individualized demands are not being met by the straightforward application of filters to photographs or videos. The need for image processing is expanding as people believe that computers will turn real photographs into creative images and further diversity the visual impacts of images [9,10].

The transfer of an artistic style from one picture A to another image B is referred to as "style transfer," also known as "image stylization." The final picture C has both the semantic information of image B and the artistic effects of image A. At this point, the widely used image processing program Photoshop can provide this effect, but using the tool takes expert knowledge to process the image and produce the desired image stylization, making it difficult for regular users to use. Since the development of style transfer algorithms, anyone may create artistic graphics.

Prior to neural networks, mathematical modeling was the primary method used to migrate an image's style, but this method could not be used to migrate numerous styles because the data was too complicated to compute. Deep learning-based algorithms [11] for picture style transfer, however, are far more effective and create stylized images with considerable superioritys with respect to of color and aesthetic elements like texture. The deep network represents an image's high-level features and combines those features in a manner commensurate with the preferences of human vision. This eliminates the need for a challenging mathematical modeling process, makes it easier to apply the deep network in various application scenarios, and is crucial for the growth of its commercial application. The aim of this work is to use deep LSTM to enhance the human eye visual effect of stylised generated images. The research on creative style transfer of digital pictures based on deep long and short term memory is significant because it fills the vacuum left by conventional approaches. By serializing and reconstructing a picture's attributes to create a new image with the right creative style, deep LSTM networks may automatically learn the link between an image's content and style. The deep LSTM-based image style transfer approach may more correctly capture an image's stylistic elements and provide a finer-grained style transformation when compared to conventional methods.

Digital picture art style transfer also has a rich potential for practical applications, which reflects its study history and relevance. Digital image art style transfer can provide artists and designers additional creative options. Digital art and image style manipulation have grown in popularity. For instance, incorporating a certain creative approach into a photography composition or a film's special effects might result in whole new visual effects and artistic expressions.

1.1. **Related Work.**

Gatys et al. [12] proposed a feature space texture model based on convolutional neural networks, which achieves the reconstruction of images, where each layer in the network has a computed feature map, and there will be some relationship between them, and the texture of the image can be reconstructed based on this relationship, and when extracting the texture, the network not only obtains more semantic information about the content image, but also ensures that the object more clarity [13,14].

Zhang et al. [15] designed a transform network to perform style migration on the images, adding a loss network after the transform network, which mainly used VGG16. Thies et al. [16] generated some sample images by letting the feed-forward convolutional network replace the white noise images in the previous network. Initially the sample images are unstyled images, later these sample images are converted to stylised images and then multiple images with different textures and sizes can be generated. Gong et al. [17] proposed a style conversion method with adaptive instance normalisation, which allows one to convert an image to one's preferred style at any time, with the central idea of adaptive instance normalisation. Lameloise et al. [18] proposed a generic framework for texture migration, which enables one to guide the generation of an image style according to one's needs. Binley et al. [19] proposed a combination of a stylised image in the feature space with a content image that matches its content to perform style migration on the matching image. This method works better and produces images of higher quality. However, since different artists will have different stroke styles, a style image is supposed to be in one artist's style, not an arbitrary image as the training set. Wang et al. [20] proposed using a random noise matrix applied to image style migration. Even though the orthogonal noise matrix is used and the feature maps before and after perturbation are different from the original ones, the Gram matrix remains unchanged. By analysing the above studies, it was found that the existing image style migration methods based on deep learning models have two problems as follows:

(1) The deep learning-based technique for transferring visual styles is a well-fitting parametric generative model. But, considering that the deep learning model has many parameters and the adjustment of weights is more complicated, it requires several iterations of experiments in order to further improve the subjective quality of stylized images, which will consume a lot of time and effort.

(2) Deep learning based image style transfer methods synthesise new stylised images through model iteration. This is an iterative and highly unstable optimisation process. At the same time, as the optimisation objective is often only approximately optimal, it will inevitably leave some noise in the white noise image, thus making the synthesised stylised image very prone to unnatural or scattered problems.

1.2. **Motivation and contribution.**

LSTM (Long Short Term Memory) [21,22] is widely used in natural language processing. For image processing, convolutional neural networks (CNNs) are commonly used. However, LSTMs can also play a role in image processing [23], and can be used in image style transfer to process the content and style representation of images, generating images with the appropriate style.

The above analysis shows that existing image style transfer methods based on deep learning have two more obvious drawbacks. Therefore, in order to address these two drawbacks, a WOA-LSTM algorithm based digital image art style transfer is proposed in this paper, with the following innovations:

(1) Considering the complexity of the circular iterative operation of the LSTM hidden layer and the characteristics of the LSTM gate structure with many parameters, this work introduces WOA for the intelligent solution of the parameters of the LSTM, thus solving the problems of many parameters and more complicated weight adjustment.

(2) Introducing a total variational regularisation based on L2 parametrization in the image style transfer process to improve the spatial smoothness of the synthesised image, thus solving the problem of unnatural or scattered images in the synthesised style.

2. A model-based iterative approach to image style transfer.

2.1. Generating models. Most of the deep learning based image style transfer methods use an iterative process of model generation.

The basic idea of model iteration-based image style transfer methods is to train a feed-forward generative model that can generate stylised images by using a large amount of image data. In this paper, the model iteration-based image style transfer methods are grouped into two categories, generative models and image reconstruction decoders, based on the differences in the way the generative models are trained.

Based on Gatys et al.'s algorithm, An et al. [24] proposed a method for image style transfer by training a generative model, referred to as fast style transfer. The feature extractor used was a pre-trained VGG-16 convolutional neural network model, as shown in Figure 1

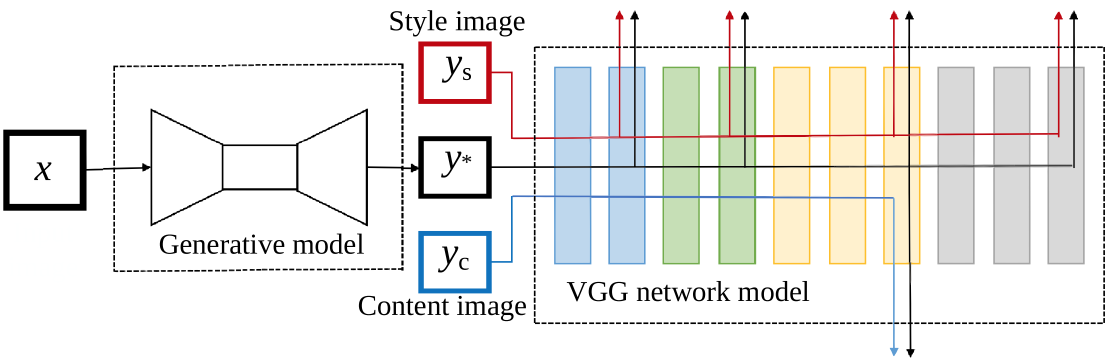


Figure 1. Fast style transfer

The generative model-based approach uses a feature extractor-based image style-aware loss function as a regularisation term and then trains a feed-forward generative model for a particular image style. When training a generative model, the common approach generally uses L1 or L2 regularisation and is done on a pixel-by-pixel basis for all pixels. The image style-aware loss function, on the other hand, is a squared difference of the high-level abstract feature representation. The definition of the total objective loss function is expressed as follows:

$$y^* = \arg\min_{f(x)} \lambda_c L_c(f(x), y_c) + \lambda_s L_c(f(x), y_s) + \lambda_{\mathrm{TV}}(f(x)) \tag{1}$$

where λ_c denotes the weight coefficients of the image content loss function, λ_s denotes the weight coefficients of the image style loss function, λ_{TV} denotes the weight coefficients of the image space smoothing loss function, x denotes the input to the generative model, $f(x)$ denotes the function of the generative model, y_c denotes the high-grade nonobjective content feature representation extracted from the content image, and y_s denotes the high-grade nonobjective style feature representation extracted from the style image.

2.2. Image reconstruction decoder. The current image iteration-based image style transfer method suffers from two drawbacks: frequent parameter tuning and computational inefficiency, while the generative model-based image style transfer method has a great improvement in computational efficiency, but the model is trained too much for a specific image style and still needs to spend a lot of time dealing with the complex and tedious parameter tuning problem.

The decoder and encoder are symmetrically reversible in the structural design of the neural network. The decoder uses an image pixel reconstruction loss function and an abstract feature matching loss function as the L2 regularisation constraints for image reconstruction. The total loss function is represented as shown below:

$$L = \|I_{\text{output}} - I_{\text{input}}\|_2^2 + \lambda \|\Phi(I_{\text{output}}) - \Phi(I_{\text{input}})\|_2^2 \tag{2}$$

where I_{input} represents the input image, I_{output} represents the output image after feature reconstruction, Φ represents the abstract feature representation extracted using the encoder corresponding to the feature extractor, and λ represents the balanced weight coefficient between the pixel reconstruction loss function and the feature matching loss function.

Given a content image, whitening and colour conversion are used to derive the content image abstraction feature H_c, and the style image abstraction feature H_s, respectively, resulting in the following stylised coding results:

$$H_{\text{cs}} = P_{\text{s}} P_{\text{c}} H_{\text{c}} \tag{3}$$

$$P_{\text{c}} = E_{\text{c}} \frac{1}{\sqrt{D_{\text{c}}}} E_{\text{c}}^{\text{T}} \tag{4}$$

$$P_{\text{s}} = E_{\text{s}} \frac{1}{\sqrt{D_{\text{s}}}} E_{\text{s}}^{\text{T}} \tag{5}$$

where D_c denotes the diagonal matrix of the covariance matrix $H_c H_c^\top$, D_s denotes the diagonal matrix of the covariance matrix $H_s H_s^\top$, E_c denotes the orthogonal matrix of the covariance matrix $H_c H_c^\top$ and E_s denotes the orthogonal matrix of the covariance matrix $H_s H_s^\top$.

The stylised image is obtained by decoding the stylised code H_{cs} using the trained decoding to obtain a synthetic image of the corresponding layer.

3. A style transfer algorithm based on improved long- and short-term memory.

3.1. LSTM neural networks. The main principle of The LSTM is comes from the recurrent neural network (RNN) [25,26] structure evolved from the recurrent neural network structure shown in Figure 2.

U, V and W are all connection weights indicating the neurons of each layer

It is clear that the output at moment t is connected to the input at moment t as well as the hidden layer output at moments *(t-1)* and *(t-2)*. The output at every instant considers the impact of the previous time sequence. By enhancing the recurrent neural network, the LSTM neural network was created. The LSTM neural network was generated by improving on the recurrent neural network. The LSTM neural network is more complex in performing recurrent operations compared to the RNN, with the introduction of storage elements and forgetting gate related operations.

The main feature of LSTM neural network, as a kind of recurrent neural network, is that the influence of historical time series is taken into account in the training process of the network, and several historical moments before the current moment are used as hidden layers for weighting training, so as to obtain the output of the current moment. The structure of the LSTM is shown in Figure 3, where f_t, i_t, o_t are the outputs of the forgetting gate, input gate and output gate at moment t, respectively; d_t is the output of the storage element at moment t; H_t, C_t denote the memory output and hidden layer output at moment t, respectively.

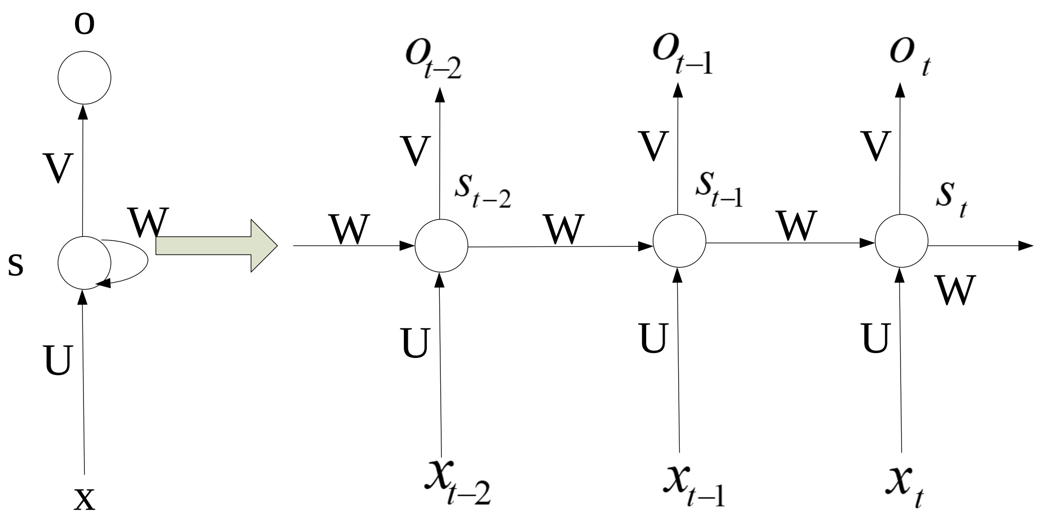


Figure 2. RNN structure

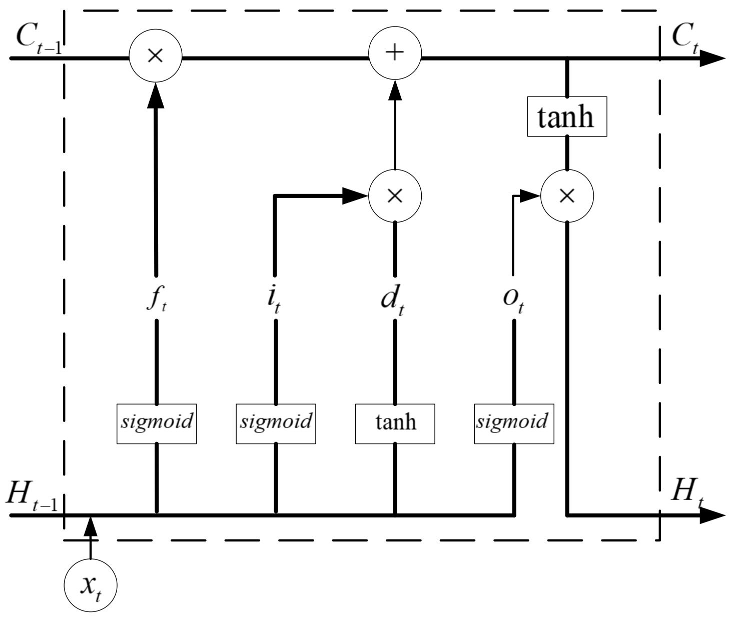


Figure 3. Structure of the LSTM

It can be seen that the LSTM network contains three structures, from left to right, forget gate, input gate and output gate. The output f_t is calculated as shown below:

$$f_t = \mathrm{sigmoid}(W_f x_t + b_f) \tag{6}$$

where W_f and b_f are the forget gate weights and biases.

The output i_t is calculated as shown below:

$$i_t = \mathrm{sigmoid}(W_i x_t + b_i) \tag{7}$$

where W_i and b_i are the weights and biases of the input gates.

The output d_t is calculated as shown below:

$$d_t = \tanh(W_c x_t + b_c) \tag{8}$$

where W_c and b_c are the weights and biases of the storage elements.

The previous moment C_{t-1} is passed through the gate structure to obtain the current moment C_t in the following way:

$$C_t = f_t C_{t-1} + i_t d_t \tag{9}$$

The output gate o_t is calculated as shown below:

$$o_t = \text{sigmoid}(W_o x_t + b_o) \tag{10}$$

where W_o and b_o are the weights and biases of the output gates.

$$H_t = o_t \tanh(C_t) \tag{11}$$

As LSTM hidden layer loop iteration operation, and the LSTM gate structure with many parameters. For example, the single hidden layer structure of the LSTM is mainly to determine (W_f, W_i, W_c, W_o) and (b_f, b_i, b_c, b_o), so the population intelligence optimization algorithm is considered to be invoked to obtain the optimized values of all the 8 parameters of the hidden layer, so as to determine the stable LSTM model structure. WOA simulates the whale hunting process to perform an optimal solution, which consists of 3 main phases: prey search, envelop predation and bubble attack. A mathematical description of these 3 phases follows.

The mathematical expression for the WOA to find the optimal solution is

$$D = |C \cdot X^*(t) - X(t)| \tag{12}$$

$$X(t+1) = X^*(t) - A \cdot D \tag{13}$$

where X^* is the optimal solution coordinates, X is the current solution coordinates, and D is the dimension of the search space, the coefficients A and C are calculated as shown below:

$$A = 2ar - a \tag{14}$$

$$C = 2r \tag{15}$$

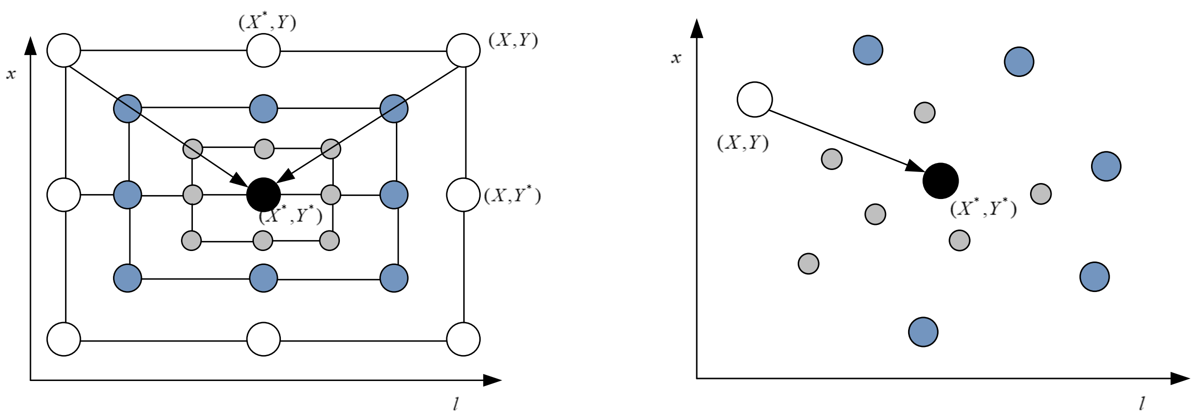
where r is the random number before [0,1] and a is the iterative reduction step length.

Using a humpback whale at X_r, as an example, the prey search method of motion is

$$D = |CX_r - X| \tag{16}$$

$$X(t+1) = X_r - A \cdot D \tag{17}$$

When a humpback whale finds its prey, it adopts 2 modes of encircling predation and spiral attack, the structure of which is shown in Figure 4.



(a) Surround search (b) Spiral search

Figure 4. WOA's prey movement patterns

The best documented whale location is indicated by the letters X^* and Y^*, which stand for its horizontal and vertical coordinates, respectively. The current whale location is indicated by the coordinates X, which represents its horizontal position, and Y, which represents its vertical position. The method of motion for a spiral attack is

$$X(t+1) = D \cdot e^{bl} \cdot \cos(2\pi l) + X^*(t) \tag{18}$$

where b is a constant, l is a random number between $[-1, 1]$.

The method of prey movement between encircling predation and spiral attack is

$$X(t+1) = \begin{cases} X^*(t) - AD & \text{if } p < 0.5 \\ D \cdot e^{bl} \cdot \cos(2\pi l) + X^*(t) & \text{if } p \geq 0.5 \end{cases} \tag{19}$$

where p is a random number between 0 and 1.

By continuously updating the position of the humpback whale and performing hunting movements according to Equation (14), iterations were made to obtain individuals with optimal fitness values.

3.2. **WOA-LSTM algorithm.** The WOA-LSTM algorithm proposed in this work uses the digitally encoded weighted sum of resource-user feature differences as the fitness function for resource recommendation optimization, and let the i-th dimensional feature difference function of both be S_i $(i = 1, 2, \ldots, N)$ and N be the total number of features, then the fitness function S is

$$\min S = \sum_{i=1}^{N} \omega_i S_i \tag{20}$$

where ω_i is the weight of the i-th dimensional eigendifference function S_i.

In the process of image style transfer using the WOA-LSTM algorithm, firstly, all pixel values are input to the LSTM network for training after variable pre-processing. Then, the input, forgetting and output gate parameters of the LSTM network are optimally solved by the WOA algorithm to obtain WOA individuals with high fitness values and stable output gate parameters. Finally, the LSTM network with the best gate parameters is adopted for iterative optimisation training of all spatial texture feature data to finally generate the synthetic map.

3.3. **Total variational regularisation.** Image noise reduction is a common technique used in image processing. In practical industrial applications, digital images are often processed with image noise due to various external factors, therefore, the use of appropriate image noise reduction has an important role in improving the quality of the image.

The fast image style transfer method starts with a white noise image and optimises iterations by fitting high-level abstract feature representations of both the content image and the style image, eventually synthesising the new stylised image. This is an iterative and highly unstable optimisation process. At the same time, as the optimisation objective can often only be approximated, the noise in the white noise image is bound to be left behind, which can easily lead to unnatural or scattered stylised images.

To address these issues, this paper adds Total Variation Regularization (TVR) based on L2 parametrization [30,31] to Gatys et al.'s algorithm to improve the spatial smoothness of synthetic images during iterative optimisation so that the problem of unnatural or scattered spots in colour-preserving image style transfer can be resolved. The use of total variance regularisation can effectively improve the spatial smoothness of stylised images. The experimental results show that in combination with the WOA-LSTM algorithm in the previous section, the total variance regularisation can effectively solve the problem of unnatural or scattered spots that occur in image style transfer.

The expression for the total variant regularization is shown below:

$$TV_{L2}(x) = \sum_{i,j} \left((x_{i,j+1} - x_{ij})^2 + (x_{i+1,j} - x_{ij})^2 \right)^{\frac{1}{2}} \tag{21}$$

where x denotes the input optimised target image (white noise image) and i and j denote the coordinate positions of the pixel points in the image respectively.

With the inclusion of the total variance cost function, the total loss function for image style transfer can be expressed as follows

$$L_t(x, x_c, x_s) = \alpha L_c(x, x_c) + \beta L_s(x, x_s) + \gamma TV(x) \tag{22}$$

where α denotes the weight coefficients of the image content loss function, β denotes the weight coefficients of the image style loss function and γ denotes the smoothing weight coefficients of the stylised image.

4. Experimental results and analysis.

4.1. Experimental environment. The experimental environment for this work is as follows:

Hardware platform: CPU is I5 12490F, memory size 8G, GPU is a GeForce NVIDIA 2080Ti GPU;

Environment configuration: Python 2.7, Tensorflow 1.12;

Operating system: Windows 10 Enterprise;

Other parameters: batch parameters of 8, training rounds of 3, learning rate of 1×10^{-3}, optimiser of stochastic gradient descent Adam, weight coefficient of the image content loss function $\alpha = 0.2$, loss function weighting factor $\beta = 0.6$, weighting factor for synthetic images $\gamma = 0.2$.

The network needs to be trained in such a way that the weighted sum of the set loss function is kept decreasing. In the experiments, part of the content image data in the training set was sourced from the network. The WikiArt dataset was used for the stylised images. The training set needs to be pre-processed to the same size before training.

4.2. Evaluation criteria. There are various criteria for good or bad image stylisation, but in the experiments of this work the main assessment is the quality effect of the stylised images. Therefore, the mean absolute value error MAE metric was used, which not only allows for a subjective human visual evaluation [32], but also incorporates an objective assessment. A smaller MAE value indicates a smaller error between the two images.The MAE is calculated as shown below:

$$MAE = \frac{1}{W \times H} \sum_{x=1}^{W} \sum_{y=1}^{H} |S(x, y) - G(x, y)| \tag{23}$$

where S is the salient plot, G is the true plot, and W and H are the width and height of the salient plot, respectively.

4.3. Experimental results. A comparative analysis with the fast style transfer algorithm was carried out and metrics were evaluated. An example of character image style transfer is shown in Figure 5.

It can be seen that the fast style transfer algorithm causes unexpected and sporadic issues in the composite image, as well as severe colour corruption in some areas of the image. This is due in large part to the fact that image colour migration is performed in the RGB colour space. Because of the strong correlation between the colour channels in the RGB colour space, colour migration can lead to colour disruption. The method

(a) Content image (b) Style image

(c) Rapid style transfer method (d) Our method

Figure 5. Example of image style transfer for people

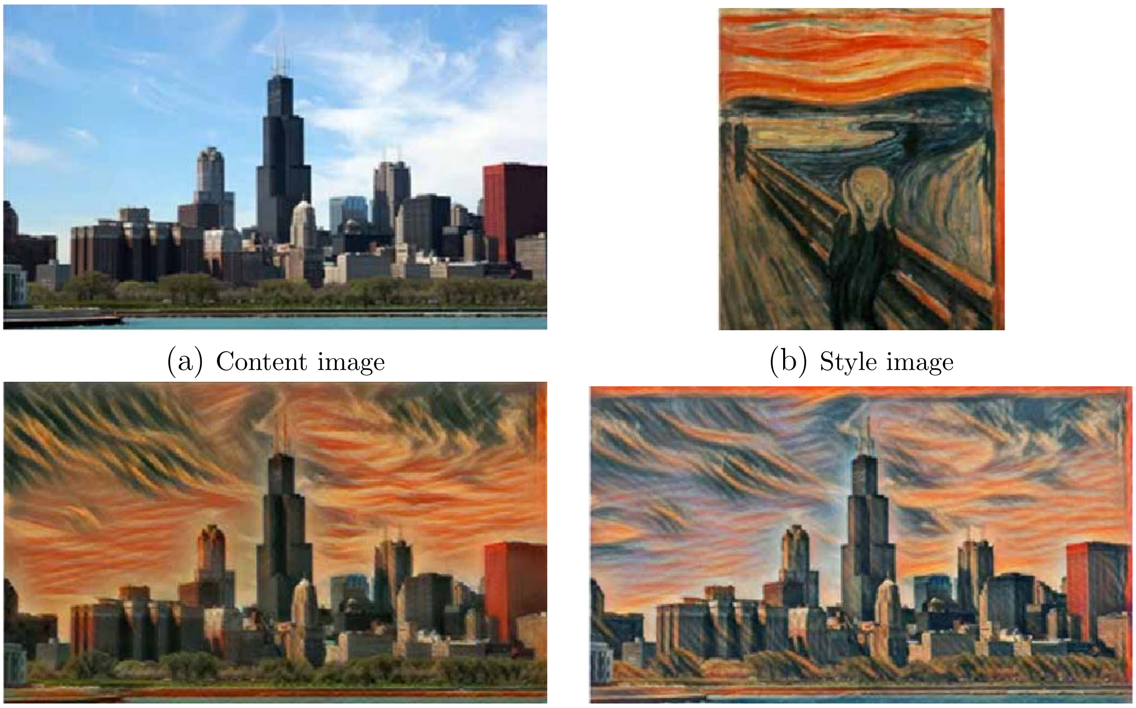
in this paper solves these problems effectively, resulting in an overall good and natural colour transition in the synthesised style image.

An example of Scream image style transfer is shown in Figure 6.

As a whole, the images generated by the different methods all have a scream image style. Although the resulting images from the fast style transfer method are more colourful, this feature also weakens some of the detail in the content image. However, our method produces an image that retains the original style and highlights the detail in the content image, resulting in a clearer overall image in comparison.

An example of Wave image style transfer is shown in Figure 7.

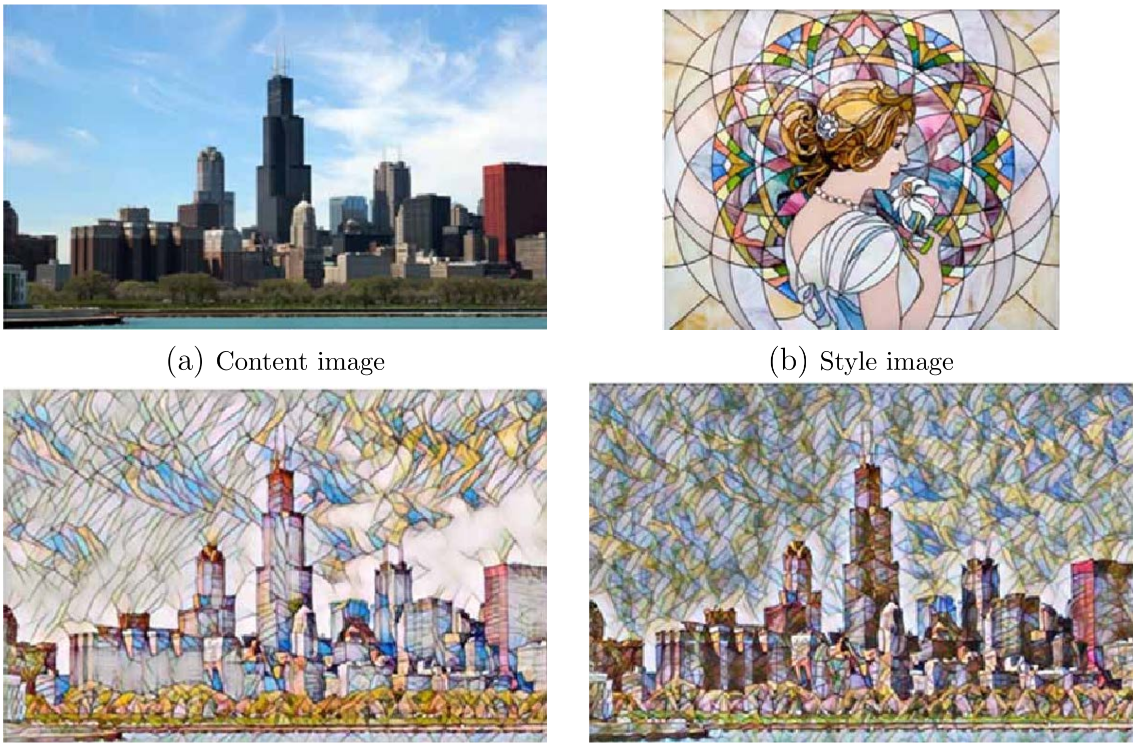
As can be seen, the overall effect of the generated map for the rapid style transfer method is better, but there are significant blank sections in the buildings. In the generated map of our method, there are no significant buildings missing, all information about the building is retained and there is no blank background.



(a) Content image (b) Style image

(c) Rapid style transfer method (d) Our method

Figure 6. Scream image style transfer example



(a) Content image (b) Style image

(c) Rapid style transfer method (d) Our method

Figure 7. Wave image style transfer example

In summary, compared to the fast style transfer method, our method does not have a blank background and the prominent regions of the content map are relatively well outlined. The MAE of each image under the different methods is shown in Table 1.

Table 1. The MAE of each image under the different methods

	Gatys et al. method	**Quick style transfer method**	**Our method**
Images of people	0.156	0.131	0.121
Scream images	0.159	0.145	0.135
Wave image	0.203	0.181	0.171
Average	0.173	0.152	0.142

The experimental results show that the proposed method has the lowest MAE values for the generated images and the MAE values are relatively stable compared to the Gatys et al. method and the fast style transfer method, regardless of the style of image processed. However, both the Gatys et al. method and the fast style transfer method have relatively high MAE values for the generated images, and also have unstable MAE values due to the migration of different styles. The average MAE of the proposed method is reduced by 6.5 % compared to the fast style transfer method, which indicates that the significant areas of the image are effectively retained.

The results of the subjective user survey are shown in Figure 8. People of different ages, occupations and genders were selected as scorers of the quality of the generated images. Each stylised image was given a full score of 10, and users were asked to rate each stylised image, mainly in terms of image quality and salient areas. Finally, the average score is calculated. It can be seen that the proposed method generates the highest scores for the stylised images, which indicates that the use of total variable score regularisation can effectively improve the spatial smoothness of the stylised images. In combination with the WOA-LSTM algorithm, the total variance regularisation can effectively solve the problem of unnatural or scattered spots in image stylised migration.

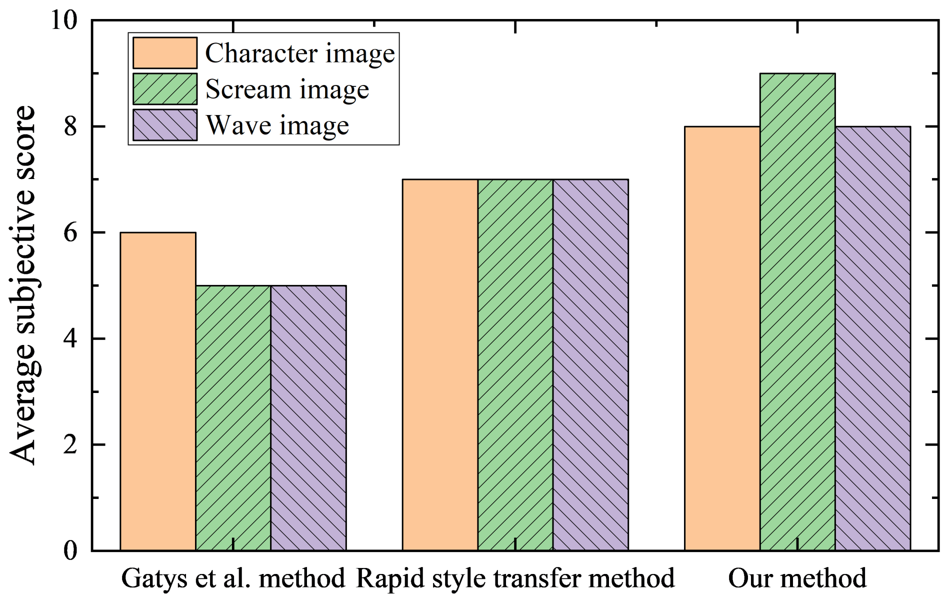


Figure 8. Subjective user survey results

5. **Conclusion.** The existing image style transfer methods based on deep learning have two more obvious drawbacks. Therefore, in order to solve these two drawbacks, a WOA-LSTM algorithm based on digital image art style transfer is proposed in this paper. Firstly, this work introduces WOA for intelligent solution of the parameters of LSTM, thus solving the problems of many parameters and more complicated weight adjustment. Secondly, a total variational regularisation based on L2 parametrization is introduced in the image style transfer process to improve the spatial smoothness of the synthesised images, thus solving the problem of unnatural or scattered images in the synthesised style. The experimental data show that the proposed method can effectively achieve image smoothing of stylised images and can effectively solve the problem of significant content distortion in the generated images. The mean absolute value error MAE is reduced by 6.5

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