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Research on Computer Algorithm for Drawing Pencil Drawing of Cold Landscape Based on Improved Neural Network Algorithm

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Abstract:

In order to face the cold landscape image, the pencil sketch image is drawn by computer algorithm. This article uses an improved neural network to complete the above process. First, we first propose a pencil drawing image generation method based on multi-level visual saliency maps. Subsequently, the corresponding stroke generation, tone mapping and texture synthesis methods are proposed to form an automatic pencil drawing generation framework, which has universal practical significance. Finally, we improved the cold landscape pencil sketch simulation method based on line integral convolution, and proposed a A new mixed noise model that replaces the random binary white noise used in the traditional pencil sketch simulation method based on line integral convolution, and also proposes a new objective evaluation measure to evaluate different noise models; experimental results It shows that the image generated by the method proposed in this paper is more layered and artistic, and closer to the painter's paintings. Experiments show that the composite frame obtained by this method can quickly convert the photo into a pencil drawing artistic style image, and the effect is vivid and lifelike.

Key-words: deep neural network; cold landscape image; pencil sketch drawing; computer simulation; salient features

1 INTRODUCTION

Since the mid-1990s, non-photorealistic rendering has gradually become a research hotspot in computer graphics [1]. Non-photo realistic rendering (NPR) is a branch of graphics corresponding to photorealistic graphics. It is usually used to express those drawing forms that are not realistic, for example, cold landscape pencil painting, watercolor painting, oil painting, ink painting, cartoon painting, etc. NPR ignores the accuracy and authenticity of the image, and through abstract art forms, more It shows the content and style of the image well and conveys the designer's thoughts. At present, it has been widely used in computer animation, digital film, architectural design, art design, data visualization, image processing, etc [2]. With the development of digital photography technology and Internet technology with the development, the demand for the generation of artistic stylized images in these fields is becoming stronger and stronger, so the research of NPR has important significance and broad prospects. In recent years, many domestic and foreign works have focused on automatic NPR generation technology, that is, through the original Photo images are extracted, converted, and processed to generate new non-realistic image works with artistic style [3]. Unlike photos, the generated non-realistic images emphasize the content that you want to express and remove redundant details, making it more efficient Send message.

Although the innovation of computer technology has led to the continuous improvement of cold landscape pencil sketch simulation drawing technology, the existing cold landscape pencil sketch simulation method cannot simulate the real cold landscape pencil sketch very realistically, and the drawing effect is still insufficient, and further progress is needed for the improvement. Today's mainstream cold landscape pencil sketch simulation methods can be divided into three categories [4]. The first category is the model-based pencil sketch simulation method of cold landscape. The pencil sketch of the cold landscape generated by this kind of method is more realistic, especially the visual effect is very good in the simulation of shadow tone, but it requires a lot of calculation, and sometimes requires user interaction to assist the simulation drawing. The second category is the pencil sketch simulation method of cold landscape based on deep learning. This type of method trains a large amount of data through deep neural networks to achieve the transfer of artistic style between images, but the problems of disordered strokes and unclear shadows are common in the sketch results. The third category is the image-based pencil sketch simulation method of cold landscape. This type of method takes any digital image as input, processes it through digital image processing technology, and simulates and generates an image with a pencil sketch style of cold landscape. The computational complexity is lower, the applicability is stronger, and the generated results are better than those based on the method of deep learning is clear [5]. Therefore, this article mainly studies the image-based pencil sketch simulation method of cold landscape.

Aiming at the above problems, this paper improves the pencil sketch simulation method of cold landscape based on line integral convolution: proposes a pencil drawing image generation method based on multi-level visual saliency maps. This method uses a method that does not rely on data set training and learning. Based on the saliency algorithm of quantum cutting, and improve the method to calculate at multiple levels, and finally synthesize a multi-level visual importance map. This article finally quantifies the multi-level visual importance map into 3 layers: Background, foreground and details, and based on these three levels, propose corresponding stroke generation, tone mapping and texture synthesis methods to form an automatic pencil drawing generation framework, which is of universal practical significance [6]. Subsequently, this paper proposes a method based on experimental analysis The new mixed noise model replaces the random binary white noise used in the traditional pencil sketch simulation method based on line integral convolution, and also proposes a new objective evaluation measure to evaluate different noise models; this paper also simulates A variety of shadow models and cold landscape pencil-type models are realized, the general law of the shadow direction of pencil sketches in real cold landscapes is analyzed, and the vector field direction of line integral convolution is improved. At the same time, this paper also proposes the use of neural network for the first time. Learn the direction of the shadow line when the artist creates a simple still life sketch, guide the drawing of the direction of the shadow line, and simulate and generate a more realistic pencil sketch of the cold landscape.

2 EXTRACTION OF REGIONAL SALIENCY FEATURES DRAWN BY PENCIL DRAWINGS OF COLD LANDSCAPE

2.1 EXTRACTION OF SALIENT REGIONS IN COLD LANDSCAPE IMAGES

Existing saliency extraction algorithms exist:

(1) Incomplete testing;

(2) The saliency map is missing the boundary;

(3) Complicated calculation;

(4) Problems such as low resolution of the output image.

The reasons for selecting the frequency coordination algorithm (FT) and the basis for parameter setting will be given below from the reasons for the above problems [7]. The FT model determines whether it is significant or not by setting a certain frequency range as a condition to meet the significance, and calculates the Euclidean distance of the mean value of brightness, color and gray. Assume that f_h is the high-frequency cut-off value and f_l is the low-frequency cut-off value. Because the subject is in the low frequency range when it is too large, problem (1) appears. Therefore, f_l should be set low enough. The edge is in the high frequency domain, and f_h is large enough to solve problem (2). In order to avoid noise being detected, the highest value in the frequency domain needs to be eliminated. At this point, a limited interval with a bandwidth of $\left[f_l, f_h\right]$ has been preliminarily determined. In order to maximize the detection effect, a fixed range is not set. In order to solve problem (3), the difference of Gaussians (Difference of Gaussians, referred to as DoG), which can be directly called in Matlab, is selected as the band-pass filter. The DoG equation is defined as:

$$DoG(x,y)=\frac{1}{2\pi}\left(\frac{1}{\sigma_1^2}e^{-\frac{\left(x^2+y^2\right)}{2\sigma_1^2}}-\frac{1}{\sigma_2^2}e^{-\frac{\left(x^2+y^2\right)}{2\sigma_2^2}}\right)=G(x,y,\sigma_1)-G(x,y,\sigma_2) \quad (1)$$

where σ_1 and σ_2 are the standard deviations of the DoG operator. When $\sigma_1>\sigma_2$, in order to obtain f_l and f_h satisfying the conditions, σ_1 is set to infinity and σ_2 is infinitely small (and vice versa). Use color and brightness as feature values to calculate the saliency. Since Lab mode has one more brightness channel

" L " than RGB mode, it is necessary to convert the smoothed image from RGB mode to Lab mode. The visual importance is judged by calculating the Euclidean distance between each point and the mean value of gray in Lab mode, the expression is as follows:

$$S(x,y)=\|I_A-G(x,y)\| (2)$$

where I_A is the average gray value of the image, $G(x,y)$ is the Lab information at the point (x,y) after smoothing, where $G(x,y)=[L_G,a_G,b_G]^T$,$\| \|$ Represents the second norm. Reference [8] in order to reduce the amount of calculation, down-sampling to compress the picture, severely reduced the picture resolution, leading to the emergence of problem (4). The FT algorithm completely retains the resolution of the original image, and the output image remains the same size as the original image. The detection result of frequency coordination algorithm is shown in Figure 1.

(a) Input image (b) Detection of saliency region (c) Extraction of saliency region

Figure 1 Detection results of frequency coordination algorithm

2.2 PENCIL DRAWING THAT EMPHASIZES THE SALIENCY AREA

When a painter draws a pencil drawing, he usually first completes the overall outline with simple lines, and then adds gathered arcs to express colors and textures. The same method is adopted when generating pencil drawings, and the line drawing and tone texture map are generated step by step.

2.2.1 Edge extraction and line drawing

In order to generate pencil outlines, many algorithms, like the reference [9], sequentially perform neon processing on the pictures, inverting and graying to obtain the outline. However, what is generated in this way is only the edge of the original image, and the edge is not the same as the outline of the sketch. The edge lines are continuous and smooth, while the outline lines of the sketch are broken and intersecting. Therefore, this model does not directly use the edge map, but generates contour strokes by edge convolution. For the extraction of edge lines, the Canny operator [10] is chosen because it is superior to edge extraction algorithms such as differential operation, Sobel operator, Prewitt and Roberts in terms of noise suppression, and the output is clear. The principle of Canny operator: Use Gaussian function to smooth the noise and calculate its gradient, combine the differential property to suppress the non-maximum value in the gradient information, and finally use a set of thresholds to remove non-edge points, leaving the edge points to connect them into an edge map.

Because the Gaussian smoothing function has been used to reduce the noise of the picture when extracting the saliency area, the noise reduction step is omitted at this stage, and the graph obtained after Gaussian smoothing is directly used as the input image, and the gradient is calculated to extract the edge. In order to generate broken and crossed contour lines with human hand-drawn style, the method of generating contour maps in reference [11] is used for reference. Firstly, the two-dimensional space is divided into eight reference directions at an interval of 22.5°. After many experiments, 1/30 of the length of the input picture is selected as the line length to generate short line segments in eight directions. The discriminant to determine which direction the line segment in the edge map belongs to is:

$$E_i=L_i*E \ (3)$$

where L_i is a short line in the i_{th} direction, where $i\in\{1,2,...,8\}$. The edge map E is convolved along 8 directions, and the corresponding line segment is defined as E_i. Use the discriminant to combine the line segments, the expression is:

$$B_i(p)=\begin{cases} E(p), if \ \arg\max_i \{E_i(p)\} \\ 0, otherwise \end{cases} \quad (4)$$

where p represents the pixel, and assign the pixels that respond to all short lines in the i_{th} direction to B_i, and output them in a combined form, and then perform the same operation in the next direction until all E_i are classified. It is worth noting that at this time, and only the image edge map is divided into 8 sub-images according to the convolution operation. In order to obtain the unique line drawing of the sketch, it is necessary to convolve B_i and L_i again:

$$P'=\sum_{i=1}^{8}\left(L_i \otimes B_i\right) \quad (5)$$

The curves in B_i are convolved into short, intersecting straight lines along the direction i, and the contour line drawing is obtained after merging. Using this method to generate the contour map, the effect is vivid and close to the hand-drawn style of human beings. For the convenience of understanding, the step diagram shown in Figure 2 is given.

(a) Input image (b) Extract edge (c) Inverse operation (d) Generate stroke

Figure 2 The line drawing process generated from the edge map

According to the NPR definition, in order for the subject to attract visual attention in the entire picture, the following settings are made: the line thickness of the salient area is 2, the length is the interval $[6,9]$, the line thickness of the background area is 1, and the length is the interval $[10,13]$. $[6,13]$ is the range of line length that has the best effect after a variety of different sizes of input pictures. The specific numerical value changes with the input picture size. Due to the strong computing power, the lines of the blurred area in the original picture in the reference [12] are also calculated, which does not meet the NPR definition. To solve this problem, different parameters are set according to whether the area is significant or not, the main body is emphasized, and the background is slightly suppressed to obtain a pencil drawing with distinct primary and secondary. The effect of pencil drawing lines emphasizing salient areas is shown in Figure 3.

(a) Input image (b) Results of reference [REF] (c) Results of proposed

Figure 3 The effect of pencil drawing lines emphasizing salient areas

2.2.2 Tone mapping and texture simulation

Reference [13] found that it is not scientific to directly generate tones from grayscale images, because the curve of grayscale images tends to be high in the middle and low on both sides, while pencil-drawn histograms only explode when they reach a certain critical value in the high-brightness area increases. This distribution law is because in pencil drawings there are few black pixels, the blank area occupies a large proportion, and the brightness value of the line is very different, resulting in a certain critical value in the bright area, the curve will rise sharply. According to this feature, Laplacian distribution, uniform distribution and Gaussian distribution are used to represent the shadow layer, middle layer and highlight layer drawn by pencil. Finally, the parameter model is used to adjust the color tone. The expression equation is as follows:

$$p_1(r)=\begin{cases}\sigma_a e^{-\frac{1-r}{\sigma_a}}, if\ \ r\le 1\\ 0, otherwise\end{cases} \quad (6)$$

$$p_2(r)=\begin{cases}\dfrac{1}{u_a-u_b}, if\ \ u_a\le r\le u_b\\ 0, otherwise\end{cases} \quad (7)$$

$$p_3(r)=\frac{1}{\sqrt{2\pi\sigma_b}}e^{-\frac{(r-v)^2}{2\sigma_b^2}} \quad (8)$$

where $p_1(r)$, $p_2(r)$ and $p_3(r)$ represent the shadow layer, middle layer and highlight layer, respectively. r is the tonal value, σ_a determines the peak value of the shadow area, and is set to 9 according to observation, and u_a and u_b determine the middle layer The hue range of is 105 and 205, respectively. The scale parameter σ_b in the Gaussian distribution is set to 11, and v is the average value of the shadow layer, which is generally 90. To map the defined tone mode to the pencil drawing, the equation is as follows:

$$p(r)=\frac{1}{N}\sum_{i=1}^{3}w_i p_i(r) \quad (9)$$

where w_i is the weight corresponding to $p_i(r)$, and N is the normalization factor with a value of 3. The original author gave a set of reference data for $w_1:w_2:w_3$ as 11:37:52 [14]. It is found that setting w_1, w_2 and w_3 as adjustable output results is better, for example: the input picture has more mid tone distribution, and w_2 can be set larger when mapping tones. In order to highlight the main body, it is necessary to deepen the hue of the salient area and at the same time weaken the hue of the background area appropriately.

The setting method is to increase the proportion of the salient areas w_2 and w_3 to make the color brighter and darker, while reducing the proportion of the background area w_1. The whitening of the picture has a visually lighter effect. According to the defined equation, a group mapping law (GML) is used to regulate the tonal value of the original picture. According to observations, when a painter draws a pencil drawing, the background area is generally filled with parallel and consistent arcs quickly. On the contrary, the main part is often drawn with great care. Therefore, for texture simulation, different texture maps are selected for filling according to the area. Figure 4 shows the results of background area filling texture and salient area filling texture. Choose the left image of Figure 4 to fill the background area, and the right image to fill the salient area. Due to different personal painting habits, you can rotate the left image to obtain textures in different directions. .

Figure 4 Background area filling texture and salient area filling texture

3 PENCIL DRAWING OF COLD LANDSCAPE BASED ON IMPROVED NEURAL NETWORK

3.1 FULLY CONVOLUTIONAL NEURAL NETWORK

In recent years, deep learning has achieved great success in the image field, especially in image recognition, target detection, image segmentation and other issues. Convolutional neural networks [15] can effectively capture the global features and context information of images. It has more advantages and better results than traditional algorithms. Fully convolutional network [16] replaces the fully connected layer with a fully convolutional layer based on the convolutional neural network structure, and successfully realizes the semantic segmentation of the image at the pixel level. Learning the law of the shadow direction of pencil sketch is actually to identify the direction of the shadow in each area of an image. This problem can be regarded as an image segmentation problem, similar to the image semantic segmentation problem processed by FCN. Therefore, this article considers using FCN to learn the direction of the shadow line and guide the drawing of the shadow line direction. Convolutional neural networks generally consist of a convolutional layer, an excitation layer, a pooling layer, and a fully connected layer. Through these multi-layer structures and a large number of parameters contained therein, it automatically learns image features from low to high layers to obtain the type of input image Probability, complete the task of image recognition.

On the basis of CNN, FCN converts the fully connected layer to a fully convolutional layer, and restores the abstract feature up-sample to the size of the input image, thereby classifying each pixel to complete the task of image segmentation. Due to the good generalization performance of VGG19, this article uses the FCN model based on the classic convolutional neural network VGG19 [17]. Figure 5 shows the network structure of the FCN. The figure lists the layers and output shapes of the VGG19 and FCN networks. Conv represents the convolutional layer, pool represents the pooling layer, FC represents the fully connected layer, and the excitation layer is omitted in the diagram. It can be seen from Figure 5 that the network structure of FCN is similar to that of VGG19. The convolutional layers of the first 16 layers are the same, and the 17th, 18th, and 19th fully connected layers in VGG19 are replaced with fully convolutional layers in FCN. Next, this article introduces the FCN based on VGG19 in detail. Convolutional layer: The convolutional layer is the core of the neural network.

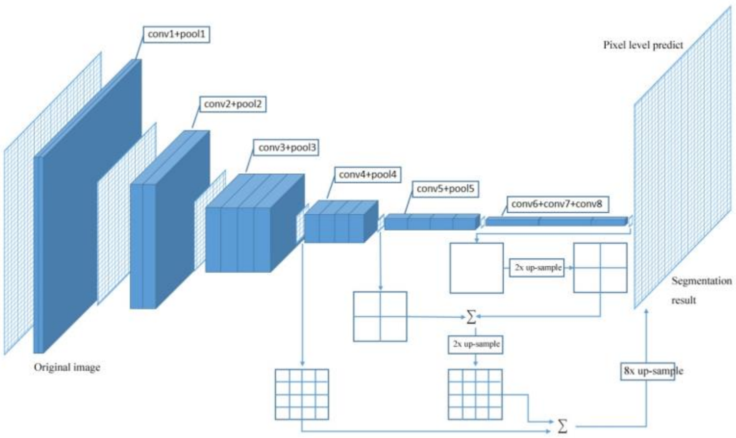


Figure 5 Architecture diagram of a fully convolutional neural network

The neural network relies on the convolution kernel in each convolution layer to perform convolution operations on the input image to extract image features. The size of the convolution kernel determines the range of image features, generally 3×3, 5×5, 7×7 and so on. Each convolutional layer contains multiple convolution kernels, so that more different features can be extracted and more feature maps can be obtained. Excitation layer: After passing through the convolutional layer, the excitation layer uses the activation function to non-linearly map the output to avoid the problem of gradient disappearance or gradient explosion in the process of gradient transmission in the multi-layer network structure. There are many types of activation functions. Commonly used are S-shaped growth curve (Sigmoid function), hyperbolic tangent function (tanh function) and linear rectification function (Rectified Linear Unit, ReLU). The activation function used by the FCN based on VGG19 is the ReLU function [18]. Pooling layer: The pooling layer compresses the feature maps obtained after the convolutional layer is processed. This operation is also called downsampling. On the basis of preserving important features, down-sampling reduces the amount of calculation, expands the receptive field for the next layer of convolution kernel, and prevents over-fitting problems. There are many methods of pooling, common ones are average pooling, maximum pooling and so on.

The pooling method used by FCN based on VGG19 is maximum pooling [19]. After each pooling, the size of the output feature map is reduced to half of the original size, as shown in Figure 5. After any image is resized, the resolution is adjusted to 224×224, as the input of FCN based on VGG19. After the first pooling, the resolution size of the feature map is reduced to 1/2 of the original resolution, which is 112×112. After the second pooling, the feature map size is halved again and reduced to 1/4 of the original resolution, which is 56×56. By analogy, after the fifth pooling, the resolution of the feature map is reduced to 1/32 of the original image, which is 7×7.

Fully convolutional layer: FCN based on VGG19 replaces the fully connected layer of VGG19 with a fully convolutional layer. As shown in Figure 5, after the fifth pooling, the resolution of the feature map is 1/32 of the original image. The final three convolutional layers conv6, conv7, and conv8 do not change the size, and the final feature map is obtained (at this time Also known as heat map), the resolution is still 1/32 of the original image. Upsampling: FCN based on VGG19 restores the feature map (heat map) to the resolution of the original image through upsampling, obtains the segmentation result map, and performs pixel-level prediction and classification.

However, the accuracy of directly up-sapmle the heat map by 32 times is not high, and the prediction result of the generated segmentation result map is not accurate. Therefore, FCN uses a parallel jump structure to up-sample the heat map, as shown in Figure 5. The heat map is up-sampled twice, and the image size becomes 1/16 of the original image size, which is the same size as the feature map after the fourth pooling [20]. Combining the two, and then up-sample them twice, the image size becomes 1/8 of the original image, which is the same size as the feature map after the third pooling. The two are fused again, and the fusion result is up-sampled 8 times, and the resulting image is the same size as the original image. Through the up-sampling method using the parallel jump structure, the segmentation result graph is more accurate than the simple 32-fold up-sampling.

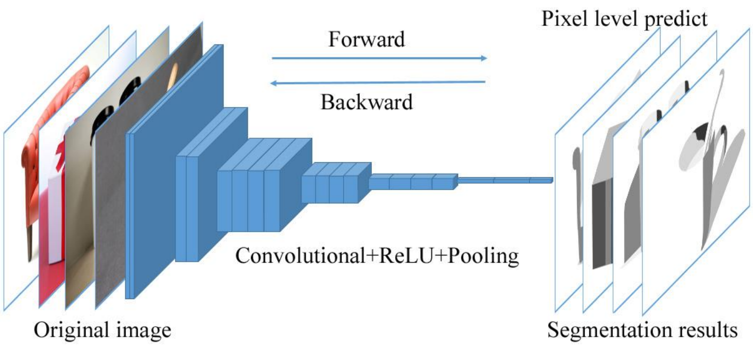
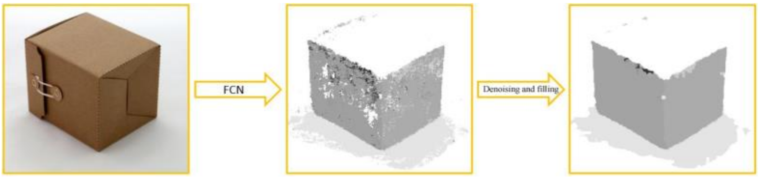


Figure 6 Sketch shadow direction learning process based on improved neural network

3.2 IMPROVED NEURAL NETWORK TO GUIDE SKETCH HATCHING

This paper uses the paired sketch shadow direction dataset constructed in FCN training section 3.1 to learn the direction of the sketch shadow. As shown in Figure 6, this article uses VGG19-based FCN to train the data set. 844 pairs of matched original images and annotated images are trained, of which 161 pairs of matching data are used as the verification set. After 100,000 iterations, the model converges and can be used for segmentation prediction. Enter any image, as shown in Figure 7(a), and you can get the segmentation result, as shown in Figure 7(b). However, the segmentation result map obtained by FCN is still very rough, as shown in Figure 7(b), which needs to be optimized. In this paper, combining the morphological operation of digital image processing and the merging algorithm of connected domains, a denoising and filling algorithm is proposed. The segmentation result after optimization of the algorithm is shown in Figure 7(c).



(a) Original image (b) Before segmentation (c) After segmentation

Figure 7 Segmentation results optimized by denoising and filling algorithm

The steps of the denoising and filling algorithm are as follows. According to the segmentation result graph, the corresponding vector field can be generated to guide the drawing of the direction of the sketch hatching. Combining the mixed noise model and LIC technology, a pencil with the hatching direction more in line with the sketching law and clear lines can be obtained. Sketch simulation results have been given.

3.3 GENERATION OF PENCIL AND BRUSH PAINTING OF COLD LANDSCAPE

The image-based pencil drawing generation process mainly includes stroke generation and tone texture generation. In the pencil brush drawing generation process, L_0 gradient minimization is used to count the sum of pixels whose gradient value is not 0 in the vertical and horizontal directions of the smoothed image. For tone and texture to generate, first use a reasonable allocation method to fully fit the light and dark tones with the original image. Then, use the exponential combination method to generate the texture of the pencil drawing, and finally fuse the stroke map and the texture map to obtain the pencil drawing generation effect [21]. The specific process of pencil drawing generation has shown in Figure 8.

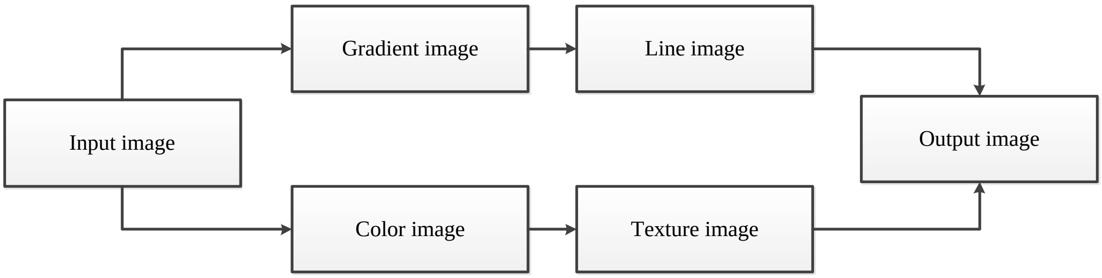


Figure 8 Computer-aided pencil drawing flow chart of cold landscape image

3.3.1 L_0 gradient minimization

The L_0 gradient minimization method is based on the L_0 norm to constrain the image gradient, which is an improved total variation (TV) model image smoothing method [22]. The processed image mainly has the following two characteristics: One is that the smoothed image and the original image are highly consistent in content structure; the other is that it can highlight the important line structure and edge information in the image [23]. Define I as the input image and S as the output image. In RGB In the vector space domain, the gradient expression of S at pixel p is $\nabla S_p = \left(\partial_x S_p, \partial_y S_p\right)^T$, and the gradient calculation expression under the L_0 constraint is:

$$C(S) = \#\{p \| \partial_x S_p | + | \partial_y S_p | \neq 0\} \quad (10)$$

where $\#\{\}$ is an operator that represents the number of gradient values in the image that are not 0. The size of $C(S)$ does not depend on the gradient magnitude, so it will not be affected by changes in the contrast of some edges in the image. Therefore, the estimated prediction of S can be obtained by the following equation:

$$S = \min_S \left\{ \sum_p \left(S_p - S_0 \right)^2 + \lambda \cdot C(S) \right\} \quad (11)$$

where S_p is the image smoothed by p times; S_0 is the original image, which does not change with the change of p; λ is a specific gravity parameter that controls the influence of $C(S)$ on the entire minimization process. λ is too large to make the processing After the image edge lines are reduced, so the value range of λ is generally between [0.01, 0.10]. This study selects as $\lambda = 0.02$. The above function cannot be solved directly because it has a problem that cannot be convexly optimized. In order to solve this problem, we expand and transform equation (12):

$$S = \min_{S,h,v} \left\{ \sum_p \left(S_p - S_0 \right)^2 + \lambda \cdot C(h,v) + \beta((\partial_x S_p - h_p)^2 + (\partial_y S_p - v_p)^2) \right\} \quad (12)$$

where the variables h_p and v_p are the approximations of the gradients $\partial_x S_p$ and $\partial_y S_p$ of S at point p in the equation (11); β is the adaptive parameter, which controls the similarity of the new variable and its corresponding gradient, from the initial The value β_0 starts to gradually increase as the iterative operation progresses. In this study, $\beta_0 = 2\lambda = 0.04$, $\beta_{\max} = 10000$. Because the L_0 gradient minimization process is too dependent on the number of non-zero gradients, it does not have good robustness.

3.3.2 Minimization of hybrid gradient

In the process of L_0 gradient minimization, h and v can be obtained by calculating the image gradient. Because the image will inevitably appear in the image due to the influence of noise, the image gradient with large calculation error will make the entire minimization process not meet the desired requirements In order to further improve the anti-interference ability of the L_0 minimization process and enhance its robustness, the L_1 norm is used as the constraint item on the basis of the original model [24]. From the smoothness of the solution of the optimization problem, the solution of L_1 norm is relatively less than the L_2 norm, but it is often the optimal solution. Although there are many solutions for the L_2 norm, they are more inclined to a certain local optimal solution. Based on the above analysis, this study adopts the following minimum mixing gradient Model:

$$S = \min_{S,h,v} \left\{ \sum_p \left(S_p - I_p \right) + \lambda \cdot C(h,v) + \beta((\partial_x S_p - h_p)^2 + (\partial_y S_p - v_p)^2) \right\} \quad (13)$$

It can be seen from equation (13) that the first part of solving S is relatively simple, and the result can be obtained directly by the gradient descent method. For the solution of h and v, only part of h and v is affected by equation (13), It can be extracted and transformed into:

$$S = \sum_p \min_{h_p, v_p} \left(\left(h_p - \partial_x S_p \right)^2 + \left(v_p - \partial_y S_p \right)^2 + \frac{\lambda}{\beta} H\left(|h_p| + |v_p| \right) \right) \quad (14)$$

where H is a binary function. When the passed parameter is not equal to 0, it returns 1, otherwise it returns 0.

Therefore, in order to obtain the minimum value, the following sub-case discussion is required:

$$\left(h_p, v_p\right) = \begin{cases} (0,0), & \left(\partial_x S_p\right)^2 + \left(\partial_y S_p\right)^2 \le \dfrac{\lambda}{\beta} \\ \left(\partial_x S_p, \partial_y S_p\right), otherwise & \end{cases} \quad (15)$$

Equation (15) is the two cases to obtain the minimum value. The values of h and v can be obtained. After the natural image is processed by the hybrid gradient minimization, the gradient value of the pixel in the image is recalculated to generate Corresponding to the contour information of the image. It can be clearly seen from the rendering in Figure 9 that the hybrid gradient minimization algorithm has a greater improvement than the L_0 gradient minimization method in terms of detail presentation and prominent lines.

(a) Original image (b) Minimize L_0 gradient (c) Results of proposed

Figure 9 The effect of stroke generation in pencil drawing of cold landscape

4 SIMULATION EXPERIMENT AND RESULT ANALYSIS

4.1 EXPERIMENTAL INITIALIZATION

The experimental environment of this article is IntelCorei7-6700CPU@3.40GHz, 32GB memory, SSD256GB hard disk, Windows1064-bit operating system, Matlab2014a. For photo images of people groups, scenery, close-up scenery, close-up people, buildings, etc., the method in this article can generate realistic pencil drawing images. There are some similarities between the method of generating automatic pencil drawings in this article and the method in [25]:

(1) All adopt the method of processing the tone and contour separately and then integrating;

(2) All use the method of stroke classification;

(3) All adopt the method of texture mapping.

However, the automatic pencil drawing generation method in this paper innovatively uses multi-level saliency maps, and proposes stroke classification, tone adjustment, and texture mapping based on multi-level saliency maps. The texture mapping in this paper is different from the reference [26] method, and its paper is not used. The conjugate gradient method mentioned in solves the fusion equation, but combines the classic texture synthesis method [27], and proposes its own texture fusion method. This article does not theoretically compare the algorithm complexity of the two methods, but in the actual experiment, texture mapping is the performance bottleneck of the entire automatic pencil drawing generation. On the same tone map, two texture mapping methods are used respectively, and the texture mapping time is counted. The performance comparison is shown in Table 1.

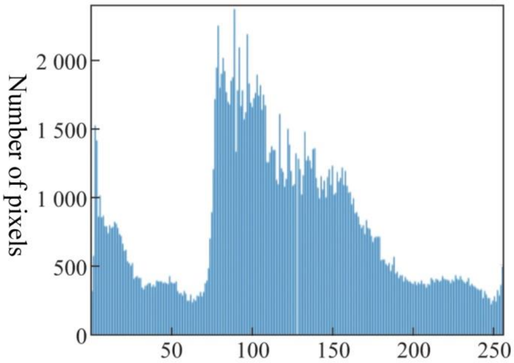
Table 1 Comparison of texture mapping performance of different methods (s)

Compared algorithms	Mapping texture time	Total computational time
Reference [27]	63.6251	64.8967
Proposed algorithm	1.5362	4.2625

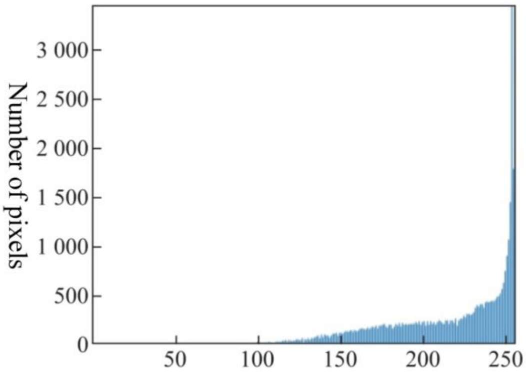
4.2 EXPERIMENTAL RESULTS AND ANALYSIS

4.2.1 Hue generation experiment results

The tones of pencil drawings are mainly composed of two parts: light and dark. In comparison, the tones of natural images are extremely rich (see Figure 10). For this reason, this research is based on the idea of binarization, and each pixel in the natural image for a certain standard is divided into light and dark areas. The simplest way to divide is to set a threshold to distinguish light and dark areas.



(a) Natural image (b) Histogram of natural image



(c) Pencil drawing image (d) Histogram of pencil drawing image

Figure 10 Comparison of natural cold landscape image and pencil drawing statistical histogram

In order to meet the needs of different preference settings, this research uses the GraphCut algorithm [28] to find the optimal threshold. Define $I(p)$ as the intensity value of the pixel p, and L_p represents the light and dark state of the pixel p (that is, when $L_p = 0$, it means dark spot, when $L_p = 1$, it means bright spot), then the energy function of pixel p is:

$$C_p(L_p, L_q) = D_p(L_p) + \alpha_s \cdot S_{(p,q)}(L_p, L_q) \quad (16)$$

where $\alpha_s \in [0,1]$ is the equilibrium constant, and the data item $D_p(L_p)$ and the stationary item $S_{(p,q)}(L_p, L_q)$ are defined as:

$$D_p(L_p) = (\alpha_g \cdot (I(p) - \phi \cdot M_g(I)) + (1-\alpha_g) \cdot (I(p) - M_l(N))) \cdot sign_D(L_p) \quad (17)$$

$$S_{(p,q)}(L_p, L_q) = \sum_{q \in N(p)} sign(L_p, L_q) \cdot \left| I(p) - I(q) \right| \quad (18)$$

where $D_p(L_p)$ represents the light and dark state of each pixel, $S_{(p,q)}(L_p, L_q)$ represents the influence of neighboring pixels on this pixel, and α_g is the weighing factor, which determines the global average intensity of $M_g(I)$.

The effect of the result, $M_l(N)$ represents the average value of the surrounding local intensity values with the pixel point p as the center (this study is set to 5×5 size), ϕ is an adjustable parameter, which can be set according to different preferences, $sign_D(L_p)$ is a signal function, and its value changes with the value of L_p, that is, when $L_p=0$, the function value is 1, when $L_p=1$, the function value is -1, and $N(p)$ represents the point near the pixel point p, When $L_p=L_q$, the value of the signal function $sign_E(L_p,L_q)$ is 0, otherwise it is 1. This study combines the classic GraphCut algorithm to determine the best segmentation of light and dark areas on the basis of minimizing the total cost of all pixels Threshold, thereby constructing a binary map to fit the tonal composition of the pencil drawing.

4.2.2 Experimental results of background texture generation

In the process of drawing pencil drawings by the artist, the background texture is often formed by repeatedly painting in the same place, and there is no specific direction and pattern. Therefore, it is very difficult to generate a suitable background texture [29]. In order to fully simulate this process, this research adopts the following index combinations:

$$H(x)^{\beta(x)} \approx J(x) \quad (19)$$

$$\beta = \arg\min \|\beta \ln H - \ln J\|_2^2 + \lambda \|\nabla \beta\|_2^2 \quad (20)$$

where J represents the final background texture map, $\lambda=0.2$. Perform repeated β operations on the input texture picture H to generate a mapping map that fits the background texture of the original image. The texture picture H in Figure 11 is a real texture image. Texture pictures H_1 and H_2 are processed by superimposing and fusion. The final texture image T is calculated by equation (21) and the size of T is consistent with the size of the contour image.

$$T = H^{\beta} \quad (21)$$

(a) Real texture H_1 (b) Real texture H_2 (c) Texture image H

Figure 11 The texture generation during the pencil drawing of the cold landscape

4.2.3 The pencil drawing of the cold landscape generates experimental results

The contour map drawn by the pencil and the tone texture map are multiplied pixel by pixel to obtain the final generated pencil drawing. At the same time, the method proposed in this research can also be extended to the generation of colored pencil drawings. When layering, only Change the brightness channel, take the generated pencil drawing as the Y channel of the original color image YUV space as input, and remap it to the RGB space to generate the effect of the color pencil drawing [30]. The pencil drawing model draws on and improves the

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reference [31], Better results have been achieved:

(1) When generating line drawings, the reference [31] uses the difference operation to extract the edge information, and replaces it with the Canny operator to extract the edge that is clearer and complete, and has better anti-noise ability;

(2) When simulating the hue, w1:w2:w3 in the reference [31] provides a fixed value for selection. The experiment found that the hue value is set to be adjustable to make the pencil drawing more bright and colorful;

(3) When simulating the texture, the reference [31] uses the conjugate gradient solution method sets different density textures. In order to simplify the experimental process, different textures are selected to directly fill different areas. The method is simpler and the effect fits the characteristics of the sketch. Through the improvement, a pencil drawing that is more in line with the definition of NPR is generated, and the requirements such as highlighting the main body and being close to human hand-drawn style are realized, as shown in Figure 12.

In terms of color pencil drawing generation, this algorithm also reflects strong detail processing capabilities. In comparison, the image processed by this algorithm is filled with just right color, the outline is clear, and the overall effect is richer and fuller (see Figure 12). In order to test the execution efficiency of this algorithm, a picture with a size of 800×600 was verified under the same hardware and software configuration, and the results are shown in Table 2. It can be seen that this algorithm is more time-consuming than the L_0 gradient minimization method. There are improvements in the above, but the efficiency of the algorithm execution needs to be further optimized and improved, and the optimization of this algorithm can be considered in the later stage and applied to mobile terminal devices.

(a) Original image (b) Results of reference [31] (c) Results of proposed

Figure 12 Comparison of the effects of this article and the reference [REF] method

Table 2 Comparison of time consumption of different cold landscape pencil drawing computer-aided drawing algorithms

Compared algorithms	Common pencil drawing	Colored pencil drawing
Reference [31]	4685.23	5689.64
Minimize of L_0 gradient	6352.21	8654.17
Proposed algorithm	5796.69	7568.49

5 CONCLUSION

Aiming at the current situation that non-photorealistic rendering is contrary to the definition of NPR, an improved algorithm is proposed. According to the feature of NPR that emphasizes the main body, the input image is divided into a salient area and a background area. The pencil sketch simulation method of cold landscape based on line integral convolution is improved, and a new mixed noise model is proposed, which replaces the random binary white noise used in the traditional pencil sketch simulation method based on line integral convolution. A new objective evaluation measure is proposed to evaluate different noise models. Set lines of different thicknesses and lengths according to the visual importance of the area to which they belong, and fill in textures with different densities, tones and directions to highlight the key points of the original image. Facing the cold landscape image, through the algorithm proposed in this paper, the pencil sketch image is drawn. A large number of experiments and comparisons show that the improved method is more in line with the definition of NPR. The main body is obvious, and the drawn lines are clear and vivid, and the texture is very close to the hand-painted style and the value of use.

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